A Data Mining-Based OLAP Aggregation of Complex Data: Application on XML Documents

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ABSTRACT

Nowadays, most organizations deal with complex data having different formats and coming from different sources. The XML formalism is evolving and becoming a promising solution for modelling and warehousing these data in decision support systems. Nevertheless, classical OLAP tools are still not capable to analyze such data. In this paper, we associate OLAP and data mining to cope advanced analysis on complex data. We provide a generalized OLAP operator, called *OpAC*, based on the AHC. *OpAC* is adapted for all types of data since it deals with data cubes modelled within XML. Our operator enables significant aggregates of facts expressing semantic similarities. Evaluation criteria of aggregates' partitions are proposed in order to assist the choice of the best partition. Furthermore, we developed a Web application for our operator. We also provide performance experiments and drive a case study on XML documents dealing with the breast cancer researches domain.

Keywords: OLAP; data warehouse; data mining; aggregation; agglomerative hierarchical clustering; evaluation of aggregates, XML documents

INTRODUCTION

Data warehouses were introduced to provide a support enabling to make decisions from huge amounts of data. A data warehouse is an analysis oriented structure that stores a large collection of subject oriented, integrated, time variant and non-volatile data (Kimball, 1996; Inmon, 1996). Online analytical processing (OLAP) is a key feature supported by most data warehouse systems. Based on visualization techniques (Maniatis et al., 2005), OLAP tools enable exploration and navigation into multidimensional data views, commonly called *data cubes*, in order to present interesting information to end users and decision makers.

A data cube is a multidimensional data model used to conceptualize data in a data warehouse (Chaudahuri & Dayal, 1997). The data cube contains *facts* or *cells* that are *measures* or values based on a set of *dimensions* where each dimension consists in a set of categorical descriptors, called *attributes*, and it may be organized within hierarchical structures. Consider for example a retail sales application where the dimensions of interest may include, *Costumer*, *Product*, *Location*, and *Time*. If the measure of interest in this application is sales amount, then an OLAP fact represents the sales measure corresponding to the previous dimensions according to a single attribute in each dimension.

Dimensions often form a hierarchy. For instance, the *Time* dimension may form a `day-month-year` hierarchy, and the *Location* dimension may form a `city-state-region` hierarchy. Dimensions allow different levels of granularity in the warehouse. For example, a `region` corresponds to a high level of granularity whereas a `city` corresponds to a low level of granularity. Classical aggregation in OLAP is considered the process of consolidating data values into a single and summarized one by moving from a hierarchical level of a dimension to a higher one. Typically, additive data are well suited to be aggregated by elementary operations (*Sum*, *Average*, *Max*, *Min* and *Count*) in a simple computation of measures. For example, a user wants to observe the *sum* of sales amount of *products* according to *years* and *regions*. This aggregation should use attributes to describe the targeted facts and make computation over their measures.

In the recent years, as more organizations see the web as an integral part of their communication and business, we have been dealing with a proliferation of new data formats. These data are complex and quite different and harder to treat than classical ones. They need new methodologies to be warehoused first, and then to be analyzed. XML (eXtensible Markup Language) is providing some promising solutions for integrating complex information from different sources and warehousing them. Many recent works have proposed some modellingapproaches for XML data warehouses (Golfarelli, Rizzi & Vrdoljak, 2001; Trujillo, Mora & Song, 2004; Pokorný, 2001; Baril & Bellahsène, 2000; Hümmer, Bauer & Harde, 2003; Rusu, Rahayu & Taniar, 2005; Nassis, Rajagopalapillai, Dillon & Rahayu, 2005). The general purpose of these approaches is to design or to feed warehouse through the XML formalism. For instance, Golfarelli et al. (2001) affirm that the use of XML will become a standard for warehousing heterogeneous and complex data in the next few years. This evolution in the way of warehousing complex data has some drawbacks on modellingand analysis tasks. In fact, classical OLAP tools are unsuitable and unable to deal with complex data. For example, when treating images, sounds, videos, texts or even XML documents, aggregating information with the classical OLAP does not make sense. Indeed, we are not able to compute a *sum* or an *average* operation over such kinds of data.

However, when users analyze complex data, they need more expressive aggregates than those created from elementary computation of additive measures. We think that OLAP facts representing complex objects need appropriate tools and new ways of aggregation since we wish to analyze them. To summarize information about complex data, we should rather gather their similar facts into a single group and separate dissimilar facts into different groups.

In this case, it is necessary to consider an aggregation by computing both descriptors and measures. Instead of grouping facts only by computing their measures, we also take their descriptors into account to obtain aggregates expressing semantic similarities. In order to do so, we intend to couple OLAP with data mining to create a new type of online aggregation of complex data.

OLAP and data mining can be viewed as two complementary fields. Associating them can be a solution to cope with their respective defects. In fact, on the one hand, when supported by database systems, OLAP has a powerful ability to organize views and structure data adapted to analysis, but it is restricted to simple navigation and exploration of data which weakens its analysis power. On the other hand, data mining is not very powerful for organizing data, but it is known for its descriptive and predictive power, which can discover knowledge from both simple and complex data. The general issue of coupling data mining with database systems was already discussed and motivated by Imielinski and Mannila (1996). The authors argue that data mining sets new challenges to database technology. Their combination will lead to a *second generation* of database systems able to manage KDD (Knowledge Discovery in Databases) applications just as classical ones manage business applications.

Furthermore, a data cube structure can provide a suitable context for applying data mining methods. More generally, the association of OLAP and data mining allows elaborated analysis tasks exceeding the simple exploration of a data cube. Our idea is to take advantage from OLAP as well as data mining techniques and to integrate them to the same analysis framework in order to analyze complex objects. In spite of the fact that both OLAP and data mining were considered two separate fields for a long, several recent works proved the capability of their association to provide interesting analysis process. In addition to these works, we have already proposed in (Messaoud, Boussaid & Rabaséda, 2004) a new OLAP operator, called *OpAC* (Operator for Aggregation by Clustering), that combines OLAP with an automatic clustering technique. We use the Agglomerative Hierarchical Clustering (AHC) as an aggregation strategy for complex data. We proved the interest of this new operator and its efficiency in creating semantic aggregates over an images data cube. More generally, the aggregates provided by *OpAC* give interesting knowledge about the analyzed domain.

In this paper, we propose a generalization of our operator which enables to deal with all types of data by handling a data cube modeled and fed directly by XML sources. In fact, since XML is able to represent and structure complex objects collected from different sources and which have different formats (Darmont, Boussaid, Bentayeb, Rabaséda & Zellouf, 2003), adapting *OpAC* to XML will lead to a considerable generalization of its analysis capability. In order to validate this generalization on a real world domain, we base our current study on screening mammography data taken from the breast cancer researches. We have structured these data as XML documents and have modeled them on a multidimensional data cube. Furthermore, we also propose some evaluation criteria that support the results of our operator. These criteria aim at assisting the user and helping him/her to choose the best partition of aggregates that will fit well with his/her analysis requirements.

The development of this paper is organized as follows. In the second section, we expose a state of the art of works that combine OLAP and data mining. In the third section, we present an overview of our approach. We also introduce the general context, the XML screening mammography data cube, and the objectives of our operator. In the fourth section, we develop a formal background of our approach. The fifth section is a presentation of the criteria we propose to evaluate the results of our approach. In the sixth section, we describe the architecture of a Web platform, called `MiningCubes`, which we have developed to validate our generalized approach. We also achieve some experiments concerning the performance and the time processing of this Web application. In the seventh section, we propose a case study on the XML documents that represent a screening mammography data cube. Finally, in the eighth section, we draw conclusions from this work and propose some future research directions.

RELATED WORK TO COUPLING OLAP AND DATA MINING

The major difficulty of combining OLAP and data mining is that traditional data mining algorithms are mostly designed with tabular datasets organized in *individuals-variables* form (Fayyad, Shapiro, Smyth & Uthurusamy, 1996). Therefore, multidimensional data are not suited for these algorithms. Nevertheless, a lot of previous works motivated and proved an interest of coupling OLAP with data mining methods. We distinguish three major approaches in this field.

The first approach tries to extend the query language of decision support systems in order to achieve data mining tasks. `DBMiner` system, proposed by Han (1998), summarizes this approach. Some extended OLAP operators perform data mining methods such as association, classification, prediction, clustering and sequencing. Han defines the `OLAP Mining` as a new concept that integrates OLAP technology with data mining techniques and allows to perform analysis on different portions and levels of abstraction of a data cube. He also introduces the `OLAM` (On-Line Analytical Mining) as a process of extracting knowledge from multidimensional databases. He expects that, in the future, `OLAM` will be a natural addition to OLAP technology that enhances the power of multidimensional data analysis. Chen, Dayal and Hsu (2000) discover behavior patterns by mining association rules about customers from transactional e-commerce data. They extend OLAP functions and use a distributed OLAP server with a data mining infrastructure and the resulting association rules are represented in particular cubes called `Association Rule Cubes`. Goil and Choudhary (1998) think that dimension hierarchies can be used to provide interesting information at multiple concept levels. Their approach summarizes information in a data cube, extends OLAP operators and mines association rules. Some other works consist in integrating mining functions in the database system using SQL. Chaudhuri (1998) argues that data mining promises a giant leap over OLAP. He proposes a data mining system based on extending SQL and constructs data mining methods over relational databases. Chaudhuri, Fayyad and Bernhardt (1997) developed a client-server middleware that performs a decision tree classifier over `MS SQL Server 7.0`. Meo, Psaila and Ceri (1996) propose a model that enables a uniform description for the problem of discovering association rules. The model also extends SQL and provides an operator called `MINE RULE`.

The second approach consists in adapting multidimensional data inside or outside the database system and applies classical data mining algorithms on the resulting datasets. This approach can be viewed according to two strategies. The first one consists in taking advantage from multidimensional database management system (MDBMS) in order to help the construction of learning models. In (Laurent, Bouchon-Meunier, Doucet, Gançarski & Marsala, 2000), the authors propose a cooperation between `Oracle Express` and a fuzzy decision tree software (`Salammbô`). This cooperation allows transferring learning tasks, storage constraints and data handling to the MDBMS. The second strategy transforms multidimensional data and makes them usable by data mining methods. For instance, Pinto et al. (2001) integrate multidimensional information in data sequences and apply on them the discovery of frequent patterns. In order to apply decision trees on multidimensional data, Goil and Choudhary (2001) flatten data cubes and extract contingency matrix for each dimension at each construction step of the tree. Chen, Zhu and Chen (2001) think that OLAP should be adopted as a pre-processing step in the knowledge discovery process. In the same context, Maedche, Hotho and Wiese (2000) combine databases with classical data mining systems by using OLAP engine as interface and treat telecommunication data. In this interface, OLAP tools create a target data set to generate new hypotheses by applying data mining methods. Tjioe and Taniar (2005) propose a method for mining association rules in data warehouses. Based on the multidimensional data organization, this method is capable of extracting associations from multiple dimensions at multiple levels of abstraction by focusing on measurements of summarized data. In order to do this, the authors propose to prepare multidimensional data for the mining process according to four algorithms: `VAvg`, `HAvg`, `WMAvg`, and `ModusFilter`. These algorithms prune all rows in the fact table which have less than the average quantity and provide an "initialized table". The latter table is used next for mining both on *non-hybrid* (non-repeatable predicate) and *hybrid* (repeatable predicate) association rules. Fu (2005) proposes an algorithm, called `CubeDT`, for constructing decision tree classifiers based on data cubes. This algorithm works on statistic trees which are representations of multidimensional data especially suitable for the construction of decision trees.

The third approach is rather based on adapting data mining methods and applying them directly on multidimensional data. Palpanas (2000) thinks that adapting data mining algorithms is an interesting solution to provide elaborated analysis and precious knowledge. Parsaye (1997) claims that decision-support applications must consider data mining within multiple dimensions. He proposes a theoretical `OLAP Data Mining System` that integrates a multidimensional discovery engine in order to perform discovery along multiple dimensions. Sarawagi, Agrawal and Megiddo (1998) propose to integrate a multidimensional regression module, called `Discovery-driven`, in OLAP servers. This module guides the user to detect relevant areas at various hierarchical levels of a cube. In (Sarawagi, 2001), the author proposes another tool called `iDiff`. It detects both relevant areas in a data cube and the reasons of their presence. The same approach was adopted by Favero and Robin (2001) to generate quantitative analysis reports from data cubes. They integrate in a platform, called `HYSSOP`, a content determination component based on data mining methods. Imielinski, Khachiyan and Abdulghani (2002) propose a generalized version of association rules called `Cubegrades`. The authors claim that association rules can be viewed as the change of an aggregate's measure due to a change in the cube's structure. They also introduce `CGQL` language for querying the `Cubegrades`. Dong, Han, Lam, Pei and Wang (2001) enhanced the `Cubegrades` and introduced constrained gradient analysis. Their proposition focuses on extracting pairs of cube cells that are quite different in aggregates and similar in dimensions. Instead of dealing with the whole cube, constraints on significance, probability, and gradient are added to limit the search range.

These previous works have proved that associating data mining to OLAP is a promising way to involve elaborated analysis tasks. They affirm that data mining methods are able to extend OLAP analysis power. In addition to these works, we have proposed in (Messaoud et al., 2004) another contribution to this field by developing an Operator for Aggregation by Clustering called *OpAC*. Besides enhancing classic OLAP with a clustering method, this operator also couples OLAP and data mining in order to deal with complex data in multidimensional context. We have shown in (Messaoud et al., 2004) the interest of applying our approach on a cube of images files, and we have proven the semantic significance of its facts' aggregates. In this paper, we propose to generalize our operator and to adapt it in order to handle XML data cubes and apply it on the breast cancer domain.

OVERVIEW AND OBJECTIVES OF OUR APPROACH

Nowadays, in almost any area of scientific research or business application domain, there is an increasing availability of data. These data are not only becoming larger in size, but also in complexity. Data have different types, come from heterogeneous sources, and are supported by different formats. Analyzing and extracting features from these data is therefore a complex task. To learn from these data, we need analysis tools that can make sense from them. OLAP is a powerful mean of exploring and extracting pertinent information from data through multidimensional analysis. In this context, data are organized in multidimensional views, commonly called data cubes. The construction of a data cube targets a precise analysis context and describes real world facts. For instance, these facts can be viewed according to several dimensions such as *costumer*, *Product*, *Location*, and *Time*. The choice of these dimensions closely depends on the user and the way (s)he would like to treat the facts analysis.

In addition to dimensions, an OLAP fact is also evaluated by a set of quantitative measures such as *revenue*, *profitability*, and *customer retention*. By organizing information into dimensions and measures, OLAP allows us to follow trends in a customer realm, spot anomalies across products, compare annual sales in a region by product line or customer type. Furthermore, a dimension is usually organized according to several hierarchies defining various levels of data granularity.

Each hierarchal level contains a set of attributes (also called *members*), and each attribute may conceptually include other attributes from the hierarchical level immediately below. For example, as the *Location* dimension may form the hierarchy `city-state-region`, the attribute *California* from the `state` level could include *Los Angeles*, *Long Beach*, *Oakland*, *San Diego*, and *Santa Monica* as attributes from the `city` level. Therefore, by moving from a hierarchical level to a higher one, attributes are gathered together into aggregates. In consequence, measures related to the attributes are computed and so information is summarized to a small number of sets.

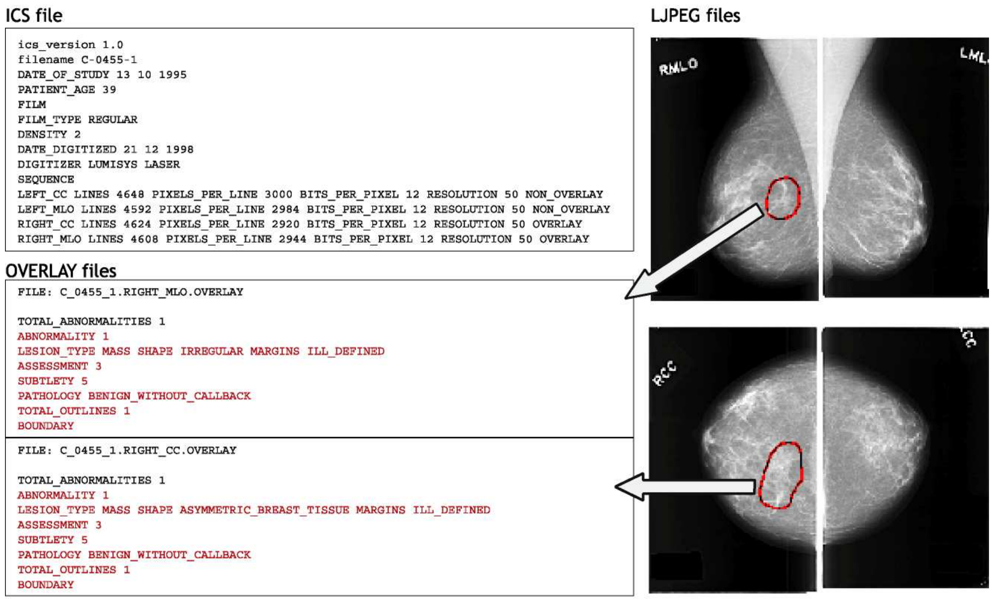
In many application domains, a user is sometimes faced to take critical decisions. Analysis tools should be efficient. For instance, aggregated measures need to reflect significant values of a set of facts sharing relation deeper than a simple order of membership. In medicine domain, experts need to see aggregates of objects, like tumors or any other pathology, that have a maximum number of common medical proprieties. For example, in the breast cancer research field, associating malign and benign patients in the same aggregate can cause dramatic consequences.

In the recent years, clinical data were widely treated by data mining techniques in medicine outcome analysis (Chen & Liu, 2005; Hu et al., 2005). In fact, medicine is one of the most important application domains where a lot of efforts are needed for structuring and analysing data in order to enhance the medical sound researches. We also propose to refer our study to an XML data cube which describes suspicious regions of tumors detected on mammography screens. We constructed this cube from the *Digital Database for Screening Mammography* (DDSM[1]). In the following, we present the DDSM and the XML data cube of the screening mammography data.

Presentation of the DDSM

The DDSM is basically a resource used by the mammographic image analysis research community in order to facilitate sound research in the development of analysis and learning algorithms (Heath, Bowyer, Kopans, Moore & Jr, 2000). The database contains approximately 2 600 studies, where each study corresponds to a patient case.

Figure 1. An Example of a patient case study from the DDSM



A patient case is a collection of image and text files containing several medical information collected along a screening mammography exam. The DDSM contains four types of patient cases: *Normal*, *Benign without callback*, *Benign*, *Cancer*. *Normal* type are mammograms from screening exams that were read as normal and had a normal screening exam. *Benign without callback* cases are exams that had an abnormality that was noteworthy but did not require the patient to be recalled for any additional workup. In *Benign* cases, something suspicious was found and the patient was recalled for some additional workup that resulted in a benign finding. *Cancer* type corresponds to cases in which a proven cancer was found.

As shows Figure 1, a case consists of a set of text and image files. There are an `ics` file (`ASCII` format) which describes general information about a patient, four `LJPEG` scanner files (image compressed with lossless JPEG encoding), and zero to four `OVERLAY` files. Only cases having suspicious regions in their scanner images are associated to overlay files. Normal cases are not. An overlay file contains information about the location, the subtlety value, and a spatial description of the marked suspicious regions. These information are specified by an expert mammography radiologist.

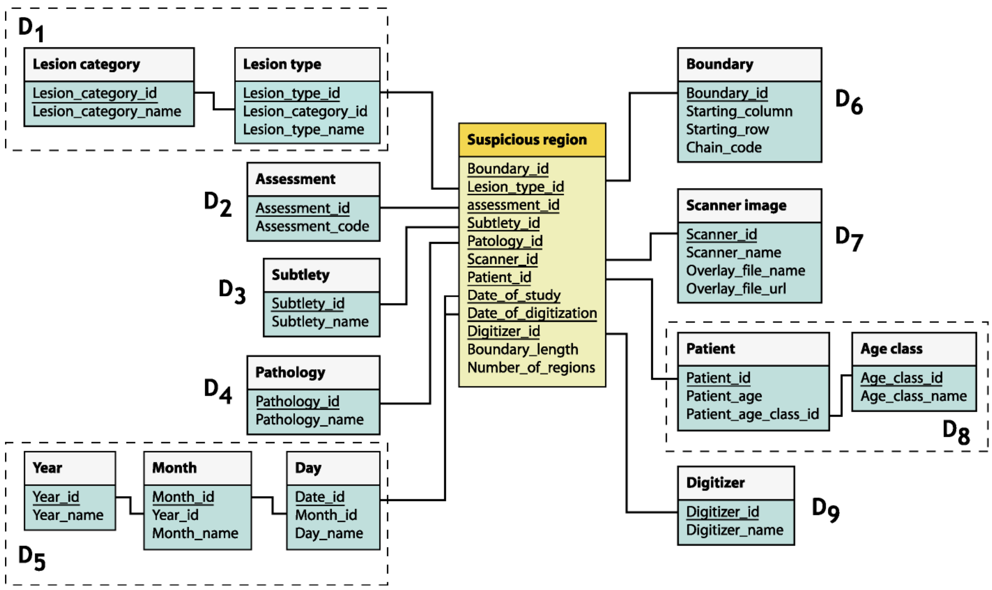
The XML Cube of the Screening Mammography Data

Since a patient study is composed by several data formats and presented on heterogeneous supports, we consider it a complex object. To warehouse and analyze such complex objects, first, we need to structure them and make them homogeneous as well as possible. In order to do so, we use XML to represent these complex data of screening mammography and model them in a data cube.

Basically, XML is considered as a particular standard syntax for the exchange of semi-structured data. The structure of XML, composed of nested custom defined tags, can describe the meaning of the content itself. XML documents can also be associated and validated against either a *Document Type Definition* (DTD) or an *XML Schema*. Both of them allow describing the structure of an XML document and to constraint its content. Nowadays, many works addressed methodologies based on XML for multidimensional design of data warehouses in order to integrate information from different sources (Golfarelli et al., 2001; Trujillo et al., 2004; Pokorný, 2001; Baril & Bellahsène, 2000; Hümmer et al., 2003; Rusu et al., 2005; Nassis et al., 2005). Since a large complex amount of data is needed in a decision making process, the importance of integrating XML in data warehousing environments is becoming increasingly high. According to Golfarelli et al. (2001), using XML sources for designing and feeding data warehouse systems will become a standard in the next few years. Furthermore, as XML source are becoming widely employed, we naturally expect important evolutions of query languages to extract knowledge from them for decision supports (Termier, Rousset & Sebag, 2002; Braga, Campi, Ceri, Klemettinen & Lanzi, 2003; Feng & Dillon, 2005).

In the case of the screening mammography data, an OLAP fact corresponds to a suspicious region (abnormality) detected by an expert. The set of collected facts concerns only *Benign*, *Benign without callback*, and *Cancer* patient cases. *Normal* cases are not concerned since they do not contain suspicious regions. As shows the conceptual model in Figure 2, a suspicious region can be analyzed according to several axes: the *lesion type*, the *assessment code*, the *subtlety*, the *pathology*, the *date of study*, the *digitizer*, the *patient age*, etc. A suspicious region is measured by the *boundary length* of its suspicious region. We have also added the *number of regions* having the same abnormality per patient as a derived measure to the data cube model.

Figure 2. Conceptual model of the screening mammography data cube



The conceptual model of the screening mammography data cube is described with an *XML Schema*. An instance of this *XML Schema* is presented by the XML document of Figure 3. The fact is associated to the root element of the *XML schema*, whereas its dimensions correspond to sub-elements. The measures of a fact are attributes in the root element, and the attribute value of each dimension is an attribute in the element corresponding to that dimension. The screening mammography data cube contains a collection of 4 686 XML documents, where each document corresponds to an OLAP fact.

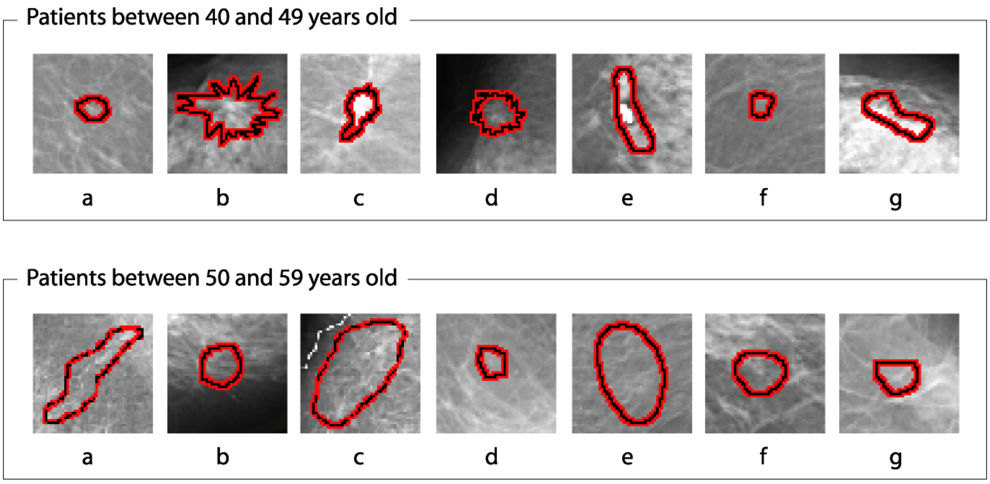
Figure 3. Example of an XML document from the screening mammography data cube


```xml
<?xml version="1.0" encoding="ISO-8859-1" ?>
<Suspicious_region Boundary_length="287" Number_of_regions="6">
        <Patient Patient_age="60" >
                <Age_class Age_class_name="Between 60 and 69 years old" />
        </Patient>
        <Lesion_type Lesion_type_name="calcification type round_and_regular distribution n/a">
                <Lesion_category Lesion_category_name="calcification type round_and_regular" />
        </Lesion_type>
        <Assessment Assessment_code="2" />
        <Subtlety Subtlety_code="4" />
        <Pathology Pathology_name="benign_without_callback" />
        <Date_of_study Date="1998-06-04">
                <Day Day_name="June 4, 1998">
                        <Month Month_name="June, 1998">
                                <Year Year_name="1998" />
                        </Month>
                </Day>
        </Date_of_study>
        <Date_of_digitization Date="1998-07-20">
                <Day Day_name="July 20, 1998">
                        <Month Month_name="July, 1998">
                                <Year Year_name="1998" />
                        </Month>
                </Day>
        </Date_of_digitization>
        <Digitizer Digitizer_name="lumisys laser" />
        <Scanner_image Scanner_name="right_cc" Overlay_file_name="B_3162_1.RIGHT_CC.LJPEG"
Overlay_file_url="ftp://figment.csee.usf.edu/pub/DDSM/cases/benign_without_callbacks/benign_without_c
allback_01/case3162/B_3162_1.RIGHT_CC.LJPEG" />
        <Boundary Starting_column="2504" Starting_row="1920" Chain_code="6 6 6 6 6 6 6 6 6 6 6 6 6
6 6 6 6 6 6 6 6 6 6 6 4 4 4 4 4 4 4 4 6 6 6 6 6 6 6 6 4 4 4 4 4 4 4 4 6 6 6 6 6 6 6 6 4 4 4 4 4 4 4 4 3 3 3 3
3 3 3 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 4 4 4 4 4 4 4 4 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1 0 0 1" />
</Suspicious_region>
```


Objectives of our Approach

In OLAP context, hierarchical structure of a dimension induces sets of attributes organized according to the logical order of membership. Through a dimension, a classical OLAP aggregation computes measures of facts and gathers these facts into groups according to the hierarchical order of their attributes in that dimension. For example, in the screening mammography data cube, according to the age class of patients, we can build aggregates of suspicious regions as those of Figure 4. In this example, we can note that, in a single aggregate, detected regions do not have relevant common medical proprieties. They have different forms and lengths of boundaries. We also note that regions of a single aggregate can have different types of lesion. Some of them can represent benign tumors while some others are cancer. For example, according to expert annotations, suspected regions (c), (e) and (g) of "*40 to 49 years old*" patients represent cancer tumors whereas the rest of regions are benign. In the aggregate "*50 to 59 years old*" patients, an expert declares that only regions (b) and (c) are cancer. This classical aggregation presented above is fully established in the conceptual step of the data cube. Therefore, it does not provide to breast cancer experts significant relations between suspicious regions.

Figure 4. Example of classical OLAP aggregation



We wish to build aggregates of objects having similar medical proprieties. In the case of the screening mammography data cube, we would like to construct more homogenous aggregates of suspected regions of tumors. These aggregates should reflect relations between objects and help experts to extract knowledge from their common proprieties.

The main idea of our operator *OpAC* is to exploit the cube's facts describing complex objects in order to provide over them a more significant aggregation. In order to do so, we use a clustering method and automatically highlight aggregates semantically richer than those provided by the current OLAP operators. So the clustering method provides a new OLAP aggregation concept. This aggregation provides hierarchical groups of objects resuming information and enables navigation through levels of these groups. Existing OLAP tools, like

Slicing operator, can create new restricted aggregates in a cube dimension, too. Therefore, these tools always need a handmade assistance, whereas our operator is based on a clustering algorithm that provides automatically relevant aggregates. Furthermore, with classical OLAP tools, aggregates are created in an intuitive way in order to compare some measure values, whereas *OpAC* creates significant aggregates that express deep relations with the cube's measures. Thus, the construction of such aggregates is interesting to establish a more elaborated on line analysis context.

According to the above objectives, we choose the AHC as an aggregation method. Our choice is motivated by the fact that the hierarchical aspect constitutes a relevant analogy between AHC results and hierarchical structures of dimensions. The objectives and the results expected for *OpAC* match perfectly with AHC strategy. Furthermore, AHC adopts an agglomerative strategy that starts by the finest partition where each individual is considered a cluster. Therefore, *OpAC* results include the finest attributes of a dimension. Moreover, AHC is compatible with the exploratory aspect of OLAP. Its results can also be reused by classical OLAP operators. In fact, AHC provides several hierarchical partitions. By moving from a partition level to a higher one, two aggregates are joined together. Conversely, by moving from a partition level to a lower one, an aggregate is divided into two new ones. These operations are strongly similar to the classical operators *Roll-up* and *Drill-down*. AHC is a well suited clustering method to summarize information into OLAP aggregates from complex facts.

FORMAL BACKGROUND OF OUR APPROACH

Individuals and Variables of the Clustering Algorithm

This formalization defines domains of individuals and variables of the clustering problem. Note that these domains are extracted from a multidimensional environment. Thus, we should respect some constraints to ensure the statistical and logical validity of the extracted data. Let Ω be the set of individuals, and Σ be the set of variables. We also assume that:

- C is a data cube having d dimensions and m measures. According to Figure 2, the XML screening mammography data cube consists of nine dimensions and two measures, in this case $d = 9$ and $m = 2$;
- $D_1, \ldots, D_i, \ldots, D_d$ are the dimensions of C. For example, in Figure 2, "*Subtlety*" dimension corresponds to D_3;
- $M_1, \ldots, M_q, \ldots, M_m$ are the measures of C. For example, in Figure 2, "*Region length*" corresponds to M_1, and "*Boundary length*" corresponds to M_2;
- $\forall i \in \{1, \ldots, d\}$, the dimension D_i contains n_i hierarchical levels. For instance, "*Patient*" dimension (D_8) of Figure 2 is composed of two hierarchical levels. So, we note $n_8 = 2$;
- h_{ij} is the j^{th} hierarchical level of D_i, where $j \in \{1, \ldots, n_i\}$;
- $\forall j \in \{1, \ldots, n_i\}$, the hierarchical level h_{ij} contains l_{ij} attributes (or members);
- g_{ijt} is the t^{th} attribute of h_{ij}, where $t \in \{1, \ldots, l_{ij}\}$;
- $G(h_{ij})$ is the set of attributes of h_{ij}.

Let suppose that we intend to aggregate attributes from level h_{ij}. So the user may choose the dimension D_i, the hierarchical level h_{ij} in D_i, and even select individuals in $G(h_{ij})$. We assume that selected attributes are elements of Ω. Therefore, we define the set of individuals as follows:

$$\Omega \subset G(h_{ij}) = \left\{ g_{ij1}, \ldots, g_{ijt}, \ldots, g_{ijl_{ij}} \right\} \quad (1)$$

Now, we adopt the following notations:

- $*$ is a meta-symbol indicating the total aggregate of a dimension;
- $\forall q \in \{1, \ldots, m\}$, we define the measure M_q as the function: $M_q : G \longrightarrow \Re$.

As shows Formula (2), G is the set of d-tuples of all the hierarchical level's attributes of the cube C including the total aggregates of dimensions:

$$\begin{aligned} G &= \prod_{i=1}^{d} \left(\underbrace{G(h_{ij})}_{j \in \{1,\ldots,n_i\}} \cup \{*\} \right) \\ G &= \left(\underbrace{G(h_{1j})}_{j \in \{1,\ldots,n_1\}} \cup \{*\} \right) \times \ldots \times \left(\underbrace{G(h_{ij})}_{j \in \{1,\ldots,n_i\}} \cup \{*\} \right) \times \ldots \times \left(\underbrace{G(h_{dj})}_{j \in \{1,\ldots,n_d\}} \cup \{*\} \right) \end{aligned} \quad (2)$$

For example, for the data cube of Figure 2, by using the above notations, we can say that:

- $M_1(\textit{calcification}, 2, *, \ldots, *)$ points out the aggregated value of the length of all suspicious region having *calcification* as *lesion type* and *2* as *subtlety code*;
- $M_2(*, \ldots, *, \textit{Patient between } 50 \textit{ and } 59 \textit{ years old}, \textit{lumisys laser})$ points out the *number of suspicious regions* of patients *between 50 and 59 years old*, scanned by a *lumisys laser* digitizer.

Remind that the objective of *OpAC* is to establish a semantic aggregation via a clustering technique on real data cube facts. In order to do so, we adopt the cube measures as quantitative variables describing the individuals of Ω. However, it is necessary to satisfy two fundamental constraints on variables:

- **First constraint**. Hierarchical levels belonging to the dimension D_i which is retained for the individuals can not generate variables. In fact, describing an individual by a property which contains it does not make logical sense. Conversely, a variable which specifies a property of an individual would only describe this one;
- **Second constraint**. In a dimension, only one hierarchical level should be selected to generate variables. This constraint enables the independence of variables. In fact, a value taken by an attribute from a hierarchical level can be calculated from attributes' values belonging to the lower level.

Since Ω is selected, we formulate the possible extracted set of variables Σ as defined in Formula (3):

$$\Sigma \subset \left\{ \begin{array}{l} V \,/\, \forall t \in \{1,\ldots,l_{ij}\} \\ \underbrace{V(g_{ijt})}_{j\in\{1,\ldots,n_j\}} = M_q\left(*,\ldots,*,\ \underbrace{g_{ijt}}_{j\in\{1,\ldots,n_j\}},*,\ldots,*,\ \underbrace{g_{srv}}_{r\in\{1,\ldots,n_s\}},*,\ldots,* \right) \\ \textit{with } s \neq i, \ r \textit{ is unique for each } s, v \in \{1,\ldots,l_{sr}\}, \textit{ and } q \in \{1,\ldots,m\} \end{array} \right\} \quad (3)$$

A user can define the set of variables by selecting dimensions D_s, hierarchical levels h_{sr}, and measures M_q. In order to achieve precise analysis tasks, a user may also select precise attributes g_{srv} in h_{sr}. The selection of g_{srv} depends naturally on the objectives carried out by the user.

The Agglomerative Hierarchical Clustering Algorithm

Once individuals and variables are selected, we can run the AHC algorithm. We note X the "*individuals-variables*" table. X is a (n, p) matrix. Its rows represent individuals of Ω, and its columns represent variables of Σ. We suppose that n is the number of individuals, and p is the number of variables.

Dissimilarities between all pairs of individuals are pre-computed. Thus a (n,n) dissimilarity matrix S is constructed. The dissimilarity of two individuals is computed according to a distance function. A lot of distance can be used, such as the "*Euclidian distance*". The general term of S is s_{ij}, which corresponds to the distance between the individuals i and j. The greater s_{ij} is, the less similar individuals i and j are. We sum up the AHC algorithm by the following steps:

- **Step 1**. The n individuals of X are assigned into n distinct clusters indexed by $\{A_1, A_2 \ldots, A_n\}$;
- **Step 2**. Two distinct clusters A_i and A_j are picked up such that their dissimilarity measure is the smallest;
- **Step 3**. The two clusters A_i and A_j are merged into a new cluster A_{n+1}. At each step two clusters are merged to form a new cluster. Therefore, the number of clusters is reduced by one;
- **Step 4**. Step 2 and 3 are repeated until the number of obtained clusters is reduced to a required number n_c, or the smallest dissimilarity value between clusters is dropped to a lower threshold.

In the specific context of our operator *OpAC*, it is up to the user to choose the number n_c of clusters he requires to see at the end of the AHC algorithm. Else, in a default situation, the AHC algorithm is stopped when it attends a single cluster.

EVALUATION OF AGGREGATES

Recall that we propose to use AHC as an aggregation operator over the attributes of a cube dimension. For n individuals to classify, the AHC generates n hierarchical partitions. Like almost all unsupervised mining methods, the main defect of AHC is that it does not give implicit evaluation of its results. In particular, we do not have any indicator about provided partitions of clusters. Therefore, it is quite tedious to choose the best partition suited with analysis objectives. Furthermore, the choice of the best partition is more difficult when we deal with a great number n of individuals. Usually, it is the expert who decides about the number of aggregates that corresponds both to the context and to the goal of his analysis.

In data mining literature, many efforts have provided a set of statistical measures for *cluster quality evaluation*. We emphasize that in our current study, the terms *cluster* and *class* refer to an OLAP *aggregate* provided by our operator. Note that unsupervised clustering methods lack a *universal* criterion of cluster quality. Any measure of cluster quality in this field closely depends on the way it is computed. It also depends on the orientations of user's analysis (Lamirel, François, Shehabi & Hoffmann, 2004). Hence, for our operator, we propose to use more than one quality criterion. The comparison of many criteria seems mandatory in order to study the quality of the resulting aggregates and to decide about the best partition according to user's requirements.

In the following, we present the *intra and inter-clusters inertias* (Lebart, Morineau & Fénelon, 1982) and the *Ward's method* (Ward, 1963) that we used as criteria to measure the quality of aggregates obtained by *OpAC*. In addition to these two criteria, we also propose a new criterion based on the *separability of classes* (Zighed, Lallich & Muhlenbach, 2002). In order to formulate these criteria, we assume the following notations:

- $\Omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$ is the set of individuals to cluster;
- each individual takes the weight $P(\omega)$, and it is described by p numerical variables $V_1, V_2, \ldots, V_p$;
- let $k \in \{0, \ldots, n-1\}$ be the index of AHC iterations (or partitions). $k = 0$ corresponds to the initial AHC partition where each individual represents a single cluster. In general, an iteration k corresponds to a partition with $n-k$ clusters;
- in iteration k, clusters A_i and A_j are merged together, and we move from the partition $k-1$ to the partition k. $A_1, A_2, \ldots, A_{n-k}$ represents the current partition of Ω;
- n_i is the size of the cluster A_i, i.e. the number of individuals in A_i;
- $\forall i \in \{0, \ldots, n-k\}$, the cluster A_i takes the weight $P(A_i) = \sum_{\omega \in A_i} P(\omega)$;
- $G(A_i) = \frac{1}{P(A_i)} \sum_{\omega \in A_i} P(\omega) V(\omega)$ is the gravity center of A_i;
- $G = \sum_{\omega \in \Omega} P(\omega) V(\omega)$ is the gravity center of Ω;
- d is the *Euclidian distance*, and d^2 is the *Squared Euclidian distance*.

Intra and Inter-Clusters Inertias

These criteria derive from the classical measures of inertia (Lebart et al., 1982). They consist of:

- minimizing the intra-cluster distances, i.e. the distance between individuals within a cluster;
- maximizing the inter-cluster distances, i.e. the distance between the gravity's centers of the clusters.

For a given subset of individuals A_i, the intra-cluster inertia is defined as:

$$I(A_i) = \sum_{\omega \in A_i} P(\omega) d(V(\omega), G(A_i)) \quad (4)$$

The total intra-clusters inertia of a partition k is defined by the sum of its $(n-k)$ subsets' inertia:

$$I_{intra}(k) = \sum_{i=1}^{n-k} I(A_i) \quad (5)$$

The inter-clusters inertia is defined by the weighted sum of distances between the gravity's center of Ω and the gravity's centers of all the subsets A_i of the partition k.

$$I_{inter}(k) = \sum_{i=1}^{n-k} P(A_i) d(G(A_i), G) \quad (6)$$

According to the theorem of *Huygens*, for each partition, the sum of the two inertias is constant and equal to the inertia of Ω.

$$\forall k \in \{0, \ldots, n-1\}, I_{intra}(k) + I_{inter}(k) = I(\Omega) \quad (7)$$

The intra-cluster inertia (respectively inter-clusters inertia) is an increasing (respectively decreasing) function according to the index of partitions k. Remember that the iteration k corresponds to a partition with $(n-k)$ aggregates. Therefore, the intra-cluster inertia is a decreasing function according to the number of aggregates. While moving from a partition to another, a remarkable break point of the intra or inter-clusters inertia will be an indicator in the choice of the number of aggregates. Through these criteria, we help the user to attend a better compromise between the minimization of the intra-clusters inertia, the maximization of the inter-clusters inertia, the number of aggregates, the significance of the aggregates, and the analysis' objectives.

The intra and inter-clusters inertias may present some limits since they have a monotonous general trend. We also propose to use the Ward's method which is another way of evaluating the AHC result's by measuring its "*merging cost*" when moving from a partition to another.

Ward's Method

The Ward's methods, proposed in (Ward, 1963), constructs a criterion that considers what happens to the sum of squared deviations from the gravity centers of two merged clusters A_i and A_j. This "*merging cost*" turns to calculate the *Squared Euclidian distance* between the gravity center's of the merged clusters weighted according to their respective sizes at each AHC iteration. The formula of this criterion is written as follows:

$$W(A_i, A_j) = \frac{n_i\, n_j}{n_i + n_j} d^2(G(A_i), G(A_j)) \quad (8)$$

At each AHC iteration, this criterion measures variation of internal inertia when two clusters are merged together. Recall that the aim is to find a partition where its clusters are as homogenous as possible. This leads to minimize the internal inertia of clusters. Therefore, when the Ward's method provides a high criterion at iteration k, it implies a great variation of internal inertia when moving from a partition $k-1$ to a partition k. This variation is quite an indicator that helps users to prefer the previous partition $k-1$ which corresponds to $(n-k+1)$ aggregates. In general, the Ward's method provides more than one relevant variation in a hierarchical clustering. Once again, it is up to users to choose the best partition that provides the best solution to the analysis' objectives.

Note that the two previous criteria are mainly related to the principle of inertia which measures the homogeneity of clusters. In order to provide a complementary way of evaluating aggregates, we propose a new alternative criterion that rather measures the quality of aggregates according to the propriety of separability of classes (Zighed et al., 2002).

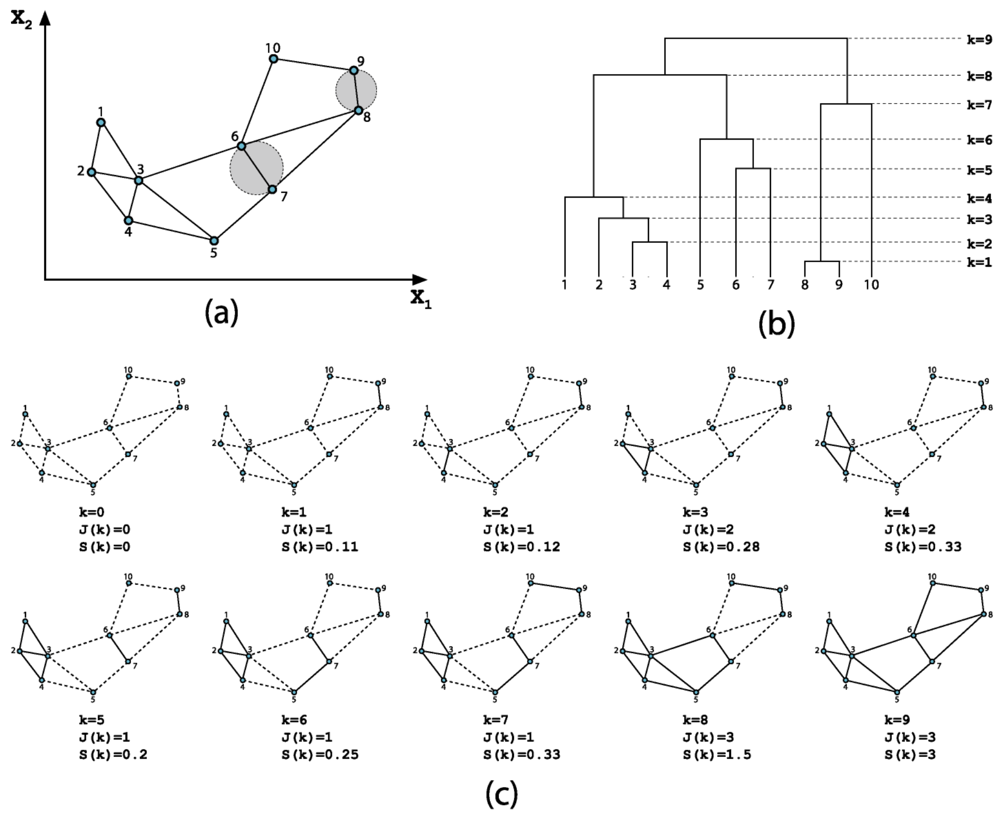
Separability Based Criterion

This criterion is derived from the method of separability of classes basically introduced by Zighed et al. (2002). This criterion starts by constructing a neighborhood graph for the whole set of objects to aggregate.

A neighborhood graph, also called a *proximity graph*, is a visual presentation which displays the overall arrangement of individuals in their space representation. In such a graph, individuals are presented by points, and two points are connected by an edge if they are, by a certain measure, close together. Specifically, two points are linked together if there are no other points in a certain forbidden region defined by these two points.

The *Gabriel graph* is a particular case of neighbourhood graphs proposed in (Gabriel & Sokal, 1969). It has been studied in the field of classification as a way to edit and condense large data sets. In the *Gabriel graph*, two points A and B are connected if their diametral sphere (i.e. the sphere such that AB is its diameter) does not contain any other points. Figure 5 (a) shows a plane representation of a *Gabriel graph* constructed on a set of objects described by two variables X_1 and X_2.

Figure 5: Principle of the separability based criterion



We assume that g_Ω is the *Gabriel graph* constructed on the whole set Ω of individuals. At each AHC iteration $k \in \{0,\ldots,n-1\}$, our criterion consists in building for each constructed cluster A_i ($i \in \{1,\ldots,n-k\}$) its own *Gabriel graph* noted g_{A_i}. Remark that:

$$\bigcup_{i=1}^{n-k} \{ g_{A_i} \} \neq g_\Omega$$

In fact, in a partition of individuals, the union of sub-graphs of its clusters A_i ($i \in \{1,\ldots,n-k\}$) does not correspond to the whole graph of Ω.

Let e_{ij}, also noted $\{ \omega_i \leftrightarrow \omega_j \}$, be the edge that connects two individuals ω_i and ω_j in a neighborhood graph. Each edge e_{ij} can be associated to a weight $P(e_{ij})$ according to the opposite *Euclidean distance* that separates its connected points ω_i and ω_j.

$$P(e_{ij}) = P\left(\left\{ \omega_i \leftrightarrow \omega_j \right\}\right) = \frac{1}{d(\omega_i, \omega_j)} \quad (9)$$

The weight associated to edges allows to quantify the importance of each connection in a neighborhood graph. In fact, two points separated by a large distance are easily separable, so their connection is relatively weak. Therefore, two close points are less separable, and their connection is quite strong. In a simple case, we can also consider that all connections in a neighbourhood graph have the same separability level. Hence, we associate the same weight ($P(e_{ij}) = 1$) for all the edges of the graph.

For each AHC iteration, the "separability based criterion" consists in computing the sum of new built connections for the *Gabriel graphs* of clusters A_i ($i \in \{1, \ldots, n-k\}$). Let ξ^k be the set of the new built edges at iteration k of the AHC. For example, according to Figure 5, at the iteration $k = 3$, the cluster 2 is merged with the cluster {3,4}. The new built connections in this case are $\{2 \leftrightarrow 3\}$ and $\{2 \leftrightarrow 4\}$. Therefore, we note $\xi^3 = \{\{2 \leftrightarrow 3\}, \{2 \leftrightarrow 4\}\}$. Let $J(k)$ be the sum of new connections of *Gabriel graphs* built at iteration k. $J(k)$ is written according to the following formula:

$$J(k) = \sum_{e \in \xi^k} P(e) \quad (10)$$

Our criterion aims at evaluation of separability of clusters for each AHC partition. Two clusters are more separable when they are connected via a small number of edges with weak connections. Nevertheless, the importance of new built edges at each iteration should also take into account the current number of clusters. Thus, the formula of our "separability based criterion" is written as follows:

$$S(k) = \frac{J(k)}{n-k} = \frac{\sum_{e \in \xi^k} P(e)}{n-k} \quad (11)$$

$S(k)$ computes, per cluster, the ratio of new built edges when AHC merges two clusters by moving from partition $(k-1)$ to k. In the criterion formula, we divide $J(k)$ by $(n-k)$ in order to get a relative evaluation of separability according to the current number of clusters. When $J(k)$ has a relative low value compared to other partitions, it means that the fact of moving from the $(k-1)$ to the k partition, weak connections are built, and therefore, the merged clusters are quite separable. So, the user may prefer to select the partition $(k-1)$ rather than the partition k. For example, Figure 5 (c) displays the process of building edges of the *Gabriel graph* at each iteration of AHC provided in Figure 5 (b). We suppose in this example that all connections have the same weight ($P(e_{ij})=1$). This example also provides the number of built edges $J(k)$ and the criterion value $S(k)$ at each step. We note that $S(k)$ marks a relative low value for the partition $k=5$. This can help the user to select the previous partition ($k=4$) with six separable clusters.

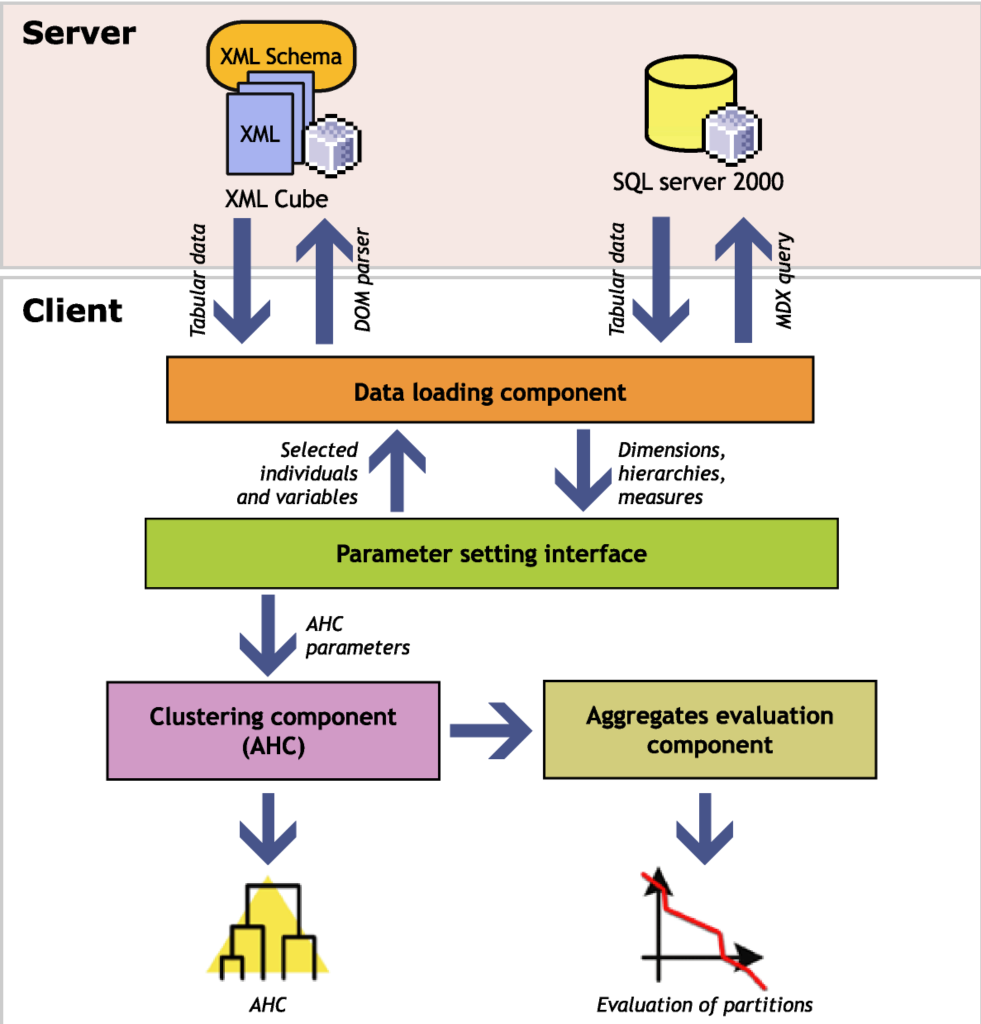
IMPLEMENTATION AND EXPERIMENTAL RESULTS

To validate our approach, we have developed a Web based environment platform called `MiningCubes`. We have included in this platform an implementation of *OpAC*. In the following, we detail the architecture of this Web application and present some performance experiments that we have led over it.

Architecture of the Web Application

`MiningCubes` contains a set of OLAP modules like a connection to classical data cubes via *MS SQL Server 2000/Analysis Services*, a connection to XML data cubes and an exploration of multidimensional data. In addition to these OLAP tools, we have also integrated analysis modules based on data mining methods. Among these, we developed a module for our operator *OpAC* which is composed of four components: a *Data loader component* from *Analysis Services of MS SQL Server 2000* or directly from XML documents, a *Parameter setting interface*, a *Clustering component* that provides aggregates of objects, and an *Aggregates evaluation component* to measure the pertinence of partitions of aggregates according to the criteria presented in the previous section. Figure 6, shows the general architecture of the *OpAC* module. In the following, we detail the functions of each component.

Figure 6: General architecture of the OpAC module



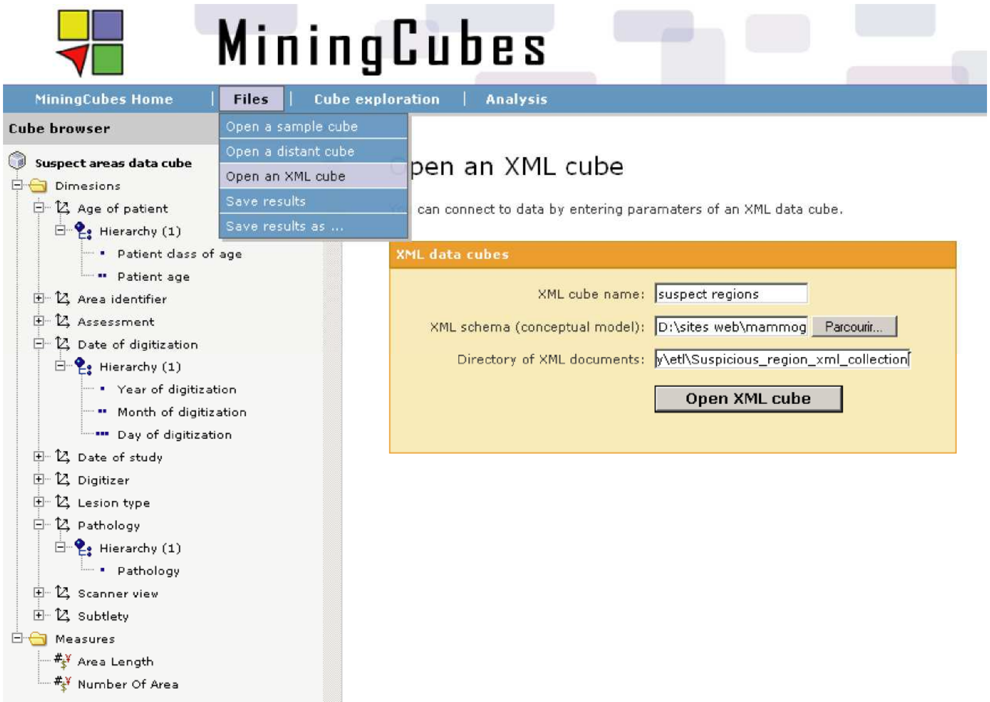
- **The data loader component**. This component connects and loads information about the structure (labels of dimensions, hierarchical levels and measures), and the content of a data cube. It can work either on a data cube stored in the *Analysis Services of MS SQL Server 2000* or directly on XML data cubes. To connect to a data cube on *Analysis Services*, the data loader component uses *MDX queries* (*Multidimensional Expressions*) to import information about the cube's structure. In the case of a connection to an XML data cube, the component uses the *DOM* (*Document Object Model*) *MSXML* to parse the XML schema that represents the conceptual model of the data cube. The *DOM* is also used to load the data of the cube from its corresponding XML documents. As the application is based on the Web technology, a user should enter, in a Web form, a cube name, its XML schema and its corresponding XML documents (see Figure 7). The application will automatically load on the Web server the XML schema, and the XML documents.

- **The parameter setting interface**. This component assists the user to extract both individuals and variables from a data cube. It enables navigation into hierarchical levels of dimensions, selection of attributes g_{ijt} for individuals, selection of attributes g_{srv}, and selection of measures M_q for the variables of the clustering problem. It also provides a user assistance respecting constraints which we have defined in the previous formalization.
- **The clustering component**. The clustering component enables the selection of the dissimilarity measure and the aggregation criterion. We implemented four dissimilarity measures (the *Euclidean Distance*, the *Squared Euclidean Distance*, the *Manhattan Distance*, and the *Chebychev Distance*), and seven aggregation criteria (the *Ward's criterion*, the *Nearest Neighbor criterion*, the *Furthest Neighbor* criterion, the *Average Distance* criterion, the *McQueen's*

criterion, the *Median Clustering* criterion, and the *Centroid Clustering* criterion). Once the user selects dissimilarity measure and the aggregation criterion, the clustering component constructs the AHC model, and plots its results within a dendrogram.

- **The aggregates evaluation component**. This component computes at each step of the AHC the criteria presented in the previous section. In fact, for each constructed partition, this component calculates inter and intra-clusters inertias, and the separability based criterion. When AHC moves from a partition to the next one, this component also calculates the sum of squared deviations according to the *Ward's method*. In the end of the AHC, the aggregates evaluation component plots the previous criteria results within graphs. Each graph presents a curve of a criterion according to partitions. This component gives an idea about the quality of AHC partitions. It also helps the user to decide about the best number of aggregates he wants to consider.

Figure 7: An XML data cube loaded by `MiningCubes`

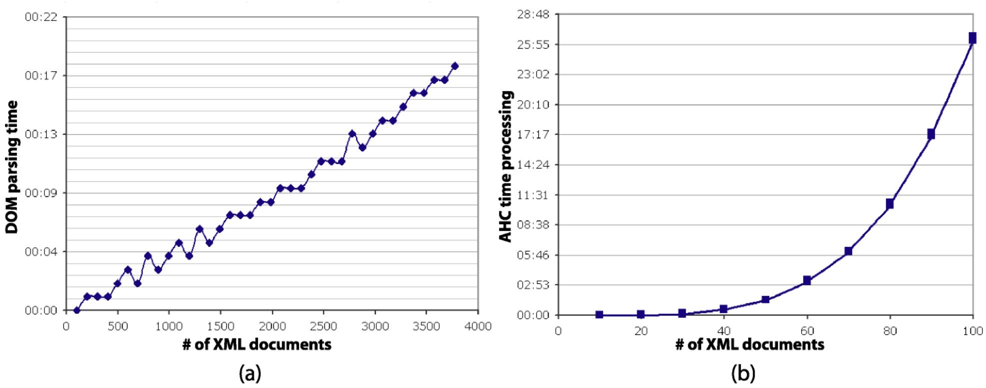


Performances of the Web Application

We have experimentally evaluated performances of our Web application within datasets of XML documents. We have constructed these datasets by a random sampling on the whole collection of OLAP facts from the screening mammography data cube presented in the third section[2]. Recall that this data cube contains 4 686 OLAP facts, where each fact is presented by an XML document as shows the example of Figure 3.

The current experiments measure times processing for different situations of input data and parameters of our operator *OpAC* supported by the Web application `MiningCubes`. We led these series of experiments under Windows XP on a 1.60 GHz PC with 480 MB of RAM, and an Intel Pentium 4 processor.

Figure 8: (a) Effect of XML documents' number on DOM parsing time. (b) Effect of XML documents' number on AHC time processing



We have measured the running time of the *data loader component* for loading XML documents, and for constructing an XML data cube. The running time of the *DOM* parser is summarized by the curve of Figure 8 (a). The general trend of the curve proves that the parsing time has a linear increasing according to the number of XML documents. Note that these experiments were achieved on *localhost*, so in a real client/server architecture, in addition to the parsing time we should also take into account the communication time of the used network.

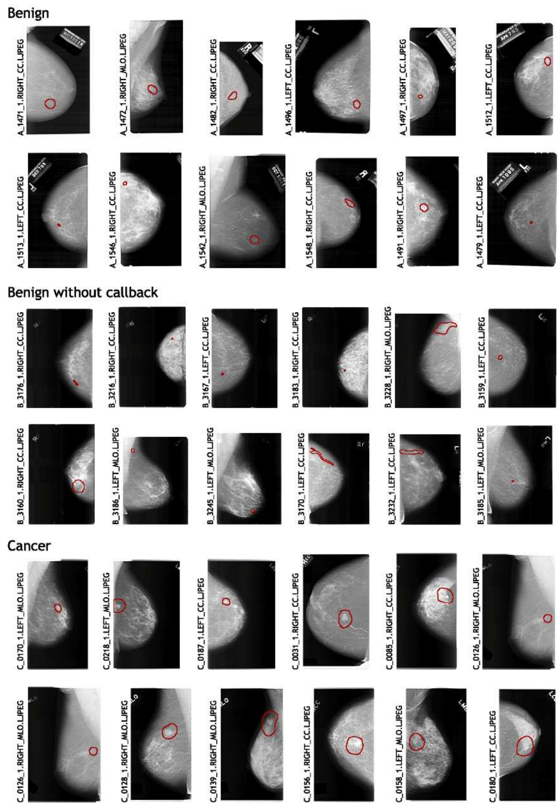
We also evaluated the time processing of the clustering component. According to Figure 8 (b), the processing time of AHC marks a polynomial increasing according to the number of documents. Indeed, there are two main expensive steps in the agglomerative clustering. The first one corresponds to the computation of the pairwise dissimilarity between all the documents. Let n be the number of XML documents to cluster, the complexity of this step is $O(n^2)$. The second step is the repeated selection of the pair of most similar clusters. During the iteration k, the AHC algorithm requires $O((n-1)^2)$ time. This lead to an overall complexity of $O(n^3)$.

Nevertheless in OLAP context, we should note that we usually deal with data cube dimensions with relatively small number of attributes. In addition, in the context of our operator, the AHC complexity would be avoided since a user focus on targeted analysis with precise, and small number, of facts to aggregate. In the next section, we introduce a real case study on the XML screening mammography data cube.

APPLICATION ON THE XML SCREENING MAMMOGRAPHY DATA CUBE

To illustrate the results of our operator, we propose to run it on the screening mammography data cube presented in Figure 2. We suppose that a user needs to create aggregates from the attributes of the *Scanner name* level (h_{71}) of the *Scanner image* dimension (D_7). We suppose that (s)he selects from $G(h_{71})$ a set of 36 mammogram scanners. Figure 9 shows the set of the selected individuals Ω.

Figure 9: The set Ω of mammogram scanners selected as individuals



In order to generate variables, suppose that the user selects the attributes of the level *Lesion type name* (h_{12}) from the *Lesion type* dimension (D_1) and the measure *Region length* (M_1). According to Formula (3), the set of variables is:

$$\Sigma = \left\{ \begin{array}{c} V_i = M_1(a_i\ , *\ , \ldots\ , *\ , \omega\ , *\ , *\ ) \\ where\ a_i \in h_{12}\ and\ \omega \in \Omega \end{array} \right\} \quad (12)$$

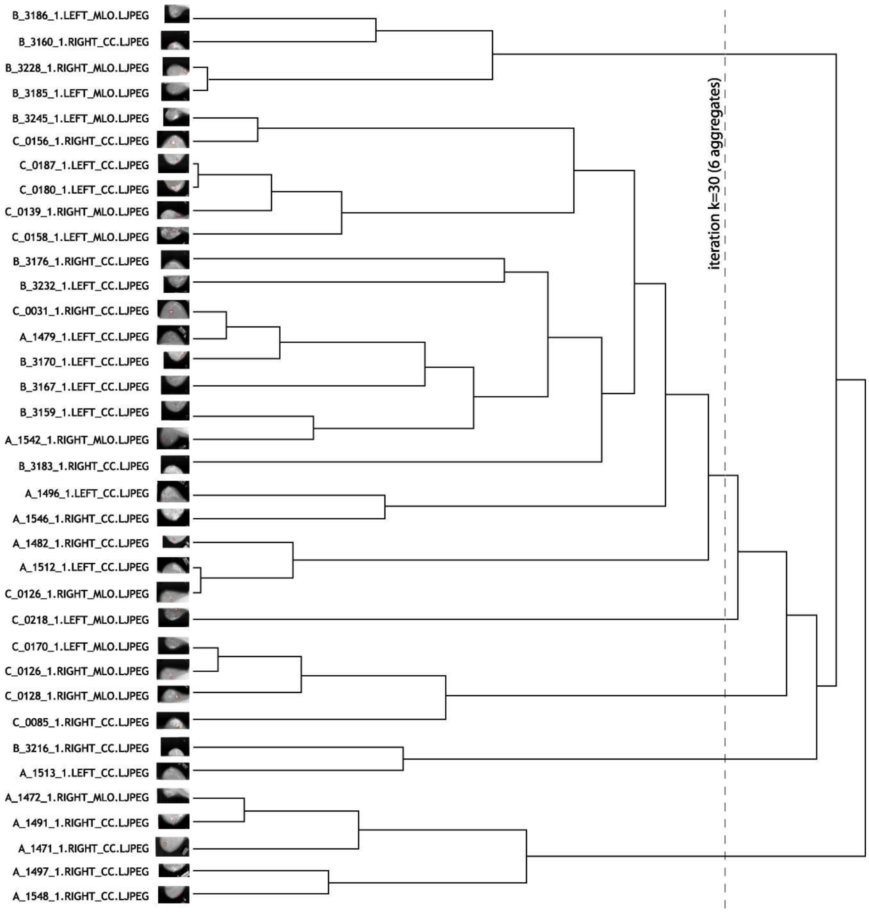
With more explicit terms, according to the available data in this case study, the set Σ contains the following 11 variables:

- V_1: *Boundary length* of suspicious region with *calcification type amorphous*
- V_2: *Boundary length* of suspicious region with *calcification type lucent center*
- V_3: *Boundary length* of suspicious region with *calcification type pleomorphic*
- V_4: *Boundary length* of suspicious region with *calcification type punctate*
- V_5: *Boundary length* of suspicious region with *calcification type skin*

- V_6: *Boundary length* of suspicious region with *calcification type vascular*
- V_7: *Boundary length* of suspicious region with *mass shape asymmetric breast tissue*
- V_8: *Boundary length* of suspicious region with *mass shape irregular*
- V_9: *Boundary length* of suspicious region with *mass shape lobulated*
- V_{10}: *Boundary length* of suspicious region with *mass shape oval*
- V_{11}: *Boundary length* of suspicious region with *mass shape round*

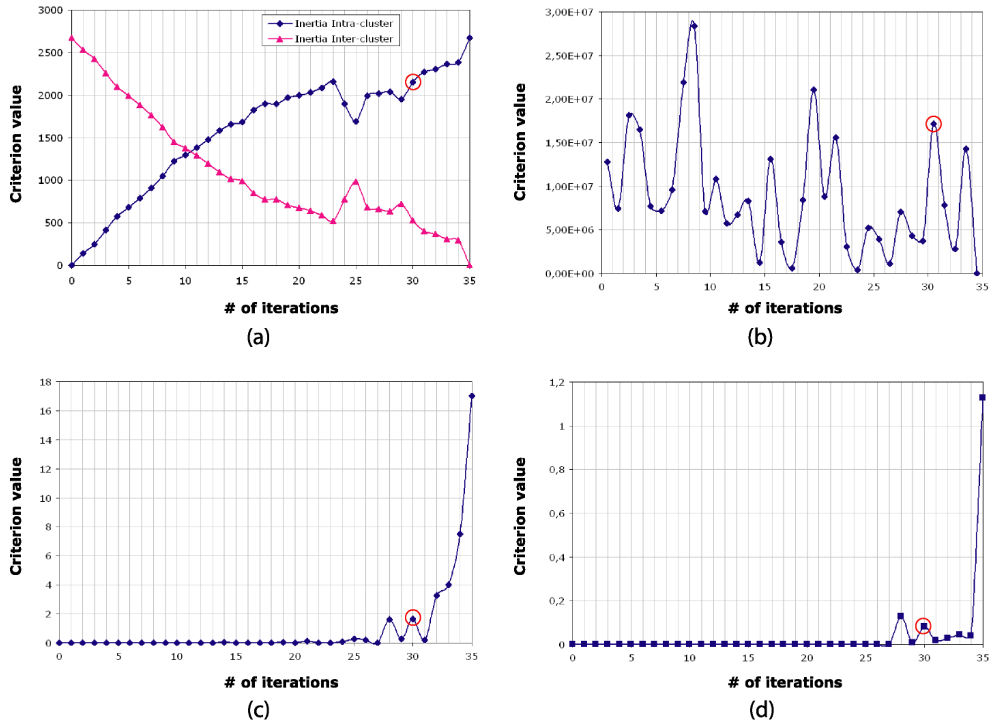
Now, suppose that the user wants to construct aggregates. If (s)he selects *Euclidean distance* as a dissimilarity metric and *Ward's criterion* as an aggregation strategy, (s)he will obtain the dendrogram of Figure 10. The user will also obtain evaluation curves of partitions according to the criteria proposed in the fifth section. Note that the obtained dendrogram is not easy to interpret. A breast cancer expert would not be able to decide about the best number of aggregates that fits with his/her analysis objectives. In this case, valuation criteria included in our operator may provide additional helps for the analysis process. Figure 11 shows resulted graphs of evaluation criteria according to the number of AHC iterations k.

Figure 10: Dendrogram generated by OpAC



We notice that all criteria release remarkable leaps for small numbers of aggregates. Generally, it is not meaningful to choose partitions with very high or very small number of aggregates. In fact, a single cluster (including the whole set of individuals) or n clusters (where each cluster contains a single individual) are two insignificant partitions for the analysis.

Figure 11: (a) Inertia intra and inter-clusters criteria (b) Ward's criterion (c) Separability based criterion (equal edges weights) (d) Separability based criterion (weighted edges) according to the growth of AHC iterations



Recall that the choice of the best partition depends on the evaluation criterion. It also depends on the analysis objectives of the user. In this case study, suppose that a breast cancer expert needs to define aggregates of similar suspicious regions. Remember again that an iteration k corresponds to a number of aggregates equal to $(n-k)$. By taking into account the previous analysis objective, an expert can choose the iteration $k=30$, which corresponds to 6 aggregates (36-30). In fact, in Figure 11 (a), the intra-cluster inertia marks a relevant increase when it moves from the iteration $k=29$ to $k=30$. The *Ward's* method, in Figure 11 (b) has an increase tendency when we move from iteration $k=30$ to $k=31$. As we need to minimize the *Ward's* indicator, the user can prefer partition of iteration $k=30$. We also see that the two separability based criterion of Figure 11 (c) and 11 (d) have relevant pics in iteration $k=30$ which comes after low values in iteration $k=29$. Furthermore, knowing that in this analysis context the clustered suspicious regions have three types of pathologies (Benign, Benign without callback, and Cancer), a breast cancer expert may need to get aggregates homogeneous as well as possible according to the type of pathology. Table 1 shows the 6 aggregates of suspicious regions that corresponds to iteration $k = 30$. We can see in this table that we obtain some aggregates with homogenous pathologies. For example, **Aggregate 1** and **Aggregate 6** consist in 100% of *Benign* suspicious regions, whereas **Aggregate 3** and the **Aggregate 4** consist in 100% of *Cancer* suspicious regions. These results may provide knowledge about similarities of suspicious regions inside each aggregate. Of course, the choice of variables is quite important for final results. The more variables are correlated with the semantic similarity we need to see in final aggregates, the more we obtain homogenous aggregates according to that similarity.

Table 1: Aggregates of suspicious regions of the AHC iteration $k = 30$

Aggregate 1 – 5 suspicious regions – 100% Benign		
A_1548_1.RIGHT_CC.LJPEG	A_1497_1.RIGHT_CC.LJPEG	A_1471_1.RIGHT_CC.LJPEG
A_1491_1.RIGHT_CC.LJPEG	A_1472_1.RIGHT_MLO.LJPEG	
Aggregate 2 – 2 suspicious regions – 50% Benign – 50% Benign without callback		
A_1513_1.LEFT_CC.LJPEG	B_3216_1.RIGHT_CC.LJPEG	
Aggregate 3 – 4 suspicious regions – 100% Cancer		
C_0085_1.RIGHT_CC.LJPEG	C_0128_1.RIGHT_MLO.LJPEG	C_0126_1.RIGHT_MLO.LJPEG
C_0170_1.LEFT_MLO.LJPEG		
Aggregate 4 – 1 suspicious region – 100% Cancer		
C_0218_1.LEFT_MLO.LJPEG		
Aggregate 5 – 20 suspicious regions – 30% Benign – 35% Benign without callback – 35% Cancer		
C_0126_1.RIGHT_MLO.LJPEG	A_1512_1.LEFT_CC.LJPEG	A_1482_1.RIGHT_CC.LJPEG
A_1546_1.RIGHT_CC.LJPEG	A_1496_1.LEFT_CC.LJPEG	B_3183_1.RIGHT_CC.LJPEG
A_1542_1.RIGHT_MLO.LJPEG	B_3159_1.LEFT_CC.LJPEG	B_3167_1.LEFT_CC.LJPEG
B_3170_1.LEFT_CC.LJPEG	A_1479_1.LEFT_CC.LJPEG	C_0031_1.RIGHT_CC.LJPEG
B_3232_1.LEFT_CC.LJPEG	B_3176_1.RIGHT_CC.LJPEG	C_0158_1.LEFT_MLO.LJPEG
C_0139_1.RIGHT_MLO.LJPEG	C_0180_1.LEFT_CC.LJPEG	C_0187_1.LEFT_CC.LJPEG
C_0156_1.RIGHT_CC.LJPEG	B_3245_1.LEFT_MLO.LJPEG	
Aggregate 6 – 4 suspicious regions – 100% Benign		
B_3185_1.LEFT_MLO.LJPEG	B_3228_1.RIGHT_MLO.LJPEG	B_3160_1.RIGHT_CC.LJPEG
B_3186_1.LEFT_MLO.LJPEG		

CONCLUSION

In this work, we propose to carry out a new on line analysis context of complex data like texts, images, sounds and videos. Our approach is based on coupling OLAP with data mining. The association of the two fields can be a solution to cope with their respective defects. We have created *OpAC*, which is a new OLAP aggregation operator based on an automatic clustering method. Unlike classical OLAP operators, our proposal enables precise analysis and provides semantic aggregates of complex objects. In this paper, we have generalized this approach and adapted *OpAC* to XML data cubes. Nowadays, XML is becoming a promising solution for warehousing complex data. We provide a formalization of our operator and define the set of individuals and variables that a user can select from a data cube. We propose criteria to evaluate the results of our operator. These criteria help users to select the best partition of aggregates that fits with their analysis requirements. Our approach is developed under a Web environment according to a client/server architecture that takes into account data cubes modelled according to XML sources. The implementation of *OpAC* is achieved in a general OLAP platform called `MiningCubes`. We have led some experiments on the developed application to evaluate the performance and the complexity of our operators. These experiments proved efficiency of our approach. They showed its capability in handling XML sources, too. We have also validated our approach through a case study on XML data cube taken from the breast cancer domain. This application has shown the interest of *OpAC* on a real world domain where decisions are quite important and sometimes critical.

This work has proved the interest of associating OLAP and data mining in order to enhance on line analysis power. We believe that, in the future, this association will provide a new generation of efficient OLAP operators adapted to complex data. For future work, a lot of issues need to be addressed. First, we need to think about an automatic approach to warehouse complex data within XML format. This warehousing step should not simply transform complex objects into XML documents and store them in a repository. It would also prepare data and represent them in an interesting way suitable to analysis and adapted to user requirements. The second issue is devoted to provide OLAP with a predictive power by associating it to a suitable data mining technique like *decision trees* or *association rules*. The third deals with the formalization of an algebra that defines a general framework of new operators that couple OLAP and data mining. This algebra should establish a generic formal background adapted to both classical and new OLAP operators.

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[1] http://marathon.csee.usf.edu/Mammography/Database.html

[2] XML documents of the screening mammography data cube are available at: http://eric.univ-lyon2.fr/~rbenmessaoud/?page=donnees&section=3