

# OLAP AGGREGATION FUNCTION FOR TEXTUAL DATA WAREHOUSE

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Abstract: For more than a decade, OLAP and multidimensional analysis have generated methodologies, tools and resource management systems for the analysis of numeric data. With the growing availability of semi-structured data there is a need for incorporating text-rich document data in a data warehouse and providing adapted multidimensional analysis. This paper presents a new aggregation function for keywords allowing the aggregation of textual data in OLAP environments as traditional arithmetic functions would do on numeric data. The AVG\_KW function uses an ontology to join keywords into a more common keyword.

## 1 INTRODUCTION

OLAP (On-Line Analytical Processing) systems allow analysts to improve decision-making process by analysing aggregated historical business data. These analyses are based on a centralized data repository, called a data warehouse (Kimball, 1996). Within data warehouses, the use of Multidimensional DataBases (MDB) enables decision-makers to gain insight into an enterprise performance.

### 1.1 Context and Motivations

Multidimensional OLAP analysis displays analysis subject data according to various levels of detail (data granularity). The process aggregates the data according to the level of detail with functions such as sum, average, maximum, minimum... Drilling operations are the most common OLAP operations. They consist in allowing the analyst to change the displayed data granularity, thus the analysed data is aggregated according to a new granularity level. In Figure 1, a decision-maker analyses the *number of keywords monthly* used by *authors*. In order to get a more global view on the data, he changes the display by *years* (he “rolls-up”). As a consequence, the monthly values are aggregated into a value for each year.

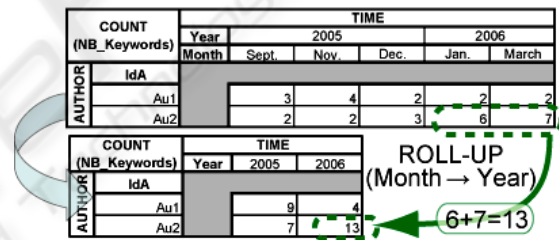


Figure 1: Multidimensional analysis of keyword counts displayed by authors and by months and rolled-up to years.

According to (Tseng and Chou, 2006) 20% of corporate information system data is transactional, i.e. numeric. This may easily be processed because multidimensional analysis is robust and it is a mastered technique on numeric-centric data warehouses (Sullivan, 2001). The remaining 80%, namely traditional “paperwork,” stays out of reach of OLAP processes due to the lack of tools and resource management for non-numeric textual data such as text-rich documents. OLAP provides powerful tools and methods but within a rigid framework. Unstructured documents do not fit in this framework. Recently, XML technology has provided a wide framework for sharing, spreading and working with documents within corporate networks or over the web. Thus, storing documents and semi-structured data was integrated within data warehouses and repositories.

Document warehousing slowly emerged as solutions were created (Sullivan, 2001), e.g. Xyleme<sup>1</sup>.

We argue that, to provide more exhaustive multidimensional analyses, OLAP decision support systems should provide the use of a 100% of corporate information system data. But, up to now, the OLAP framework lack the ability to cope with the analysis of semi-structured text-rich document data. As a consequence, there is a need for adapted conceptual models and textual aggregation processing.

## 1.2 Related Works

Related works may be divided according to two major categories. Firstly is the integration of XML data with 1) physical integration of XML data into a data warehouse. (Pokorný, 2001) builds a star schema on a logical XML structure; (Niemi et al., 2002) assembles “on the fly” XML data cubes from user queries; (Zhang et al., 2003) deals with building data warehouses on top of XML data and (Vrdoljak et al., 2003) creates a data warehouse multidimensional schema from XML schemas; and 2) the association of XML data with a data warehouse (logical integration). In (Yin and Pedersen, 2004), the authors federate XML data and traditional multidimensional data into an OLAP system. Although all these works consider textual data through the use of XML documents, they are all based on numeric-centric analysis and lack support for text-rich document-centric data analysis.

The second category concerns multidimensional analysis of documents within an OLAP framework. In (Pérez et al., 2005) the authors combine traditional numeric analysis and information retrieval techniques to assist multidimensional analysis by providing relevant documents to the ongoing analysis context. In (McCabe et al., 2000) and (Mothe et al., 2003), the authors propose the use of traditional OLAP framework to count documents according to keywords or topics in order to query more precisely a document collection. Similarly in (Chakrabarti et al., 1998) and (Agrawal et al., 2000), the authors offer tools and methods to efficiently build a hierarchical classification of documents based on typical keywords. In (Tseng and Chou, 2006) and (Keith et al., 2005), the authors suggest to build a specific keyword dimension to allow multidimensional analysis of documents. Nowadays, industrial solutions start to appear such as Text OLAP<sup>2</sup>. In (Khrouf et al., 2004) the authors describe a document warehouse where documents are grouped by similar

structures; multidimensional analysis may be performed but still with the use of numeric analysis.

These advanced propositions show the following limitations: 1) textual data is difficult to analyse as systems use numeric measures to get round the analysis of non-numeric data; 2) the most advanced systems are limited to counting keywords in document sets; and 3) non numeric indicators may not be processed. Finally, in (Park et al., 2005), the authors introduce the concept of multidimensional document analysis within an XML framework. Unfortunately, all aggregation functions using text mining techniques are not detailed.

## 1.3 Aims and Contributions

The next step of decision making is to leap ahead of numeric indicators and to allow the powerful OLAP framework to operate on non-numeric data. Contrarily to previously stated works, we wish to focus the analysis on text. Our approach has the advantage of combining qualitative analysis with quantitative analysis, e.g. the analysis of the keywords of a specific publication, in order to provide an overview of publication contents. To allow multidimensional OLAP analysis of documents, we provide an aggregation function for textual OLAP analysis. This function is based on a conceptual model that provides: 1) adapted concepts to support non-numeric textual measures; and 2) a new concept to drive OLAP textual aggregation processing with the use of a domain ontology.

The rest of this paper is organised as follows: section 2 defines the conceptual model and section 3 describes the aggregation function AVG\_KW.

## 2 CONCEPTUAL MODEL

In this section we define an extension a traditional multidimensional model to handle textual data analysis. We provide the addition of specific textual measures as well as a hierarchical representation of the analysed concepts with the use of an ontology.

### 2.1 Multidimensional Model

Multidimensional models have been used for over a decade. See (Torlone, 2003) for recent survey. Most use facts and dimensions to model multidimensional structures.

*Dimensions* model analysis axes and are composed of a set of parameters which are organised into one or more hierarchies. Each *hierarchy* represents an analysis perspective along the axis. The

<sup>1</sup> Xyleme server from <http://www.xyleme.com>

<sup>2</sup> <http://www.megaputer.com/products/pa/>

parameters represent different levels according to which analysis data may be observed.

The subject of analysis, namely a *fact*, is a conceptual grouping of measures which are numeric indicators. These *measures* are traditionally numeric and may be additive, semi-additive or non-additive (Kimball, 1996), (Horner et al., 2004). Here, analysis of textual data requires textual measures that fall into non-numeric and non-additive categories.

**Definition 1.** A *textual measure* is a measure that holds textual data, i.e. non-numeric and non-additive data.

A textual measure represents words, strings, paragraphs or even whole documents. Within these measures, we define the following categories:

**Definition 2.** A *raw textual measure* is a textual measure that corresponds to the full text of a document or to a fragment of that document.

**Definition 3.** A *keyword measure* is an elaborated textual measure, where each measure instance  $x_i$  is represented by  $x_i = (kw_i, d_i)$  such that  $kw_i$  is a keyword and  $d_i$  a distance.

Raw textual measures are provided for flexibility, allowing the user to consult document contents.

Keyword measures require a certain amount of pre-processing in order to be created. The domain of all keywords is  $dom(kw)$ . Notice that  $x_i \in X$  with  $X = dom(kw) \times \mathcal{N}$  and all distances  $d_i = 0$ , this value will be used during the aggregation process.

For example, to get a view of the subjects of a collection of scientific articles, a decision-maker analyses keywords used by authors. The fact *Articles* has a numeric measure: *Acceptance*, corresponding to the acceptance rate of each article; and two textual measures: the raw textual measure representing the complete article (*Text*) and the elaborated textual measure (*Keywords*) which holds keywords extracted from article bodies. The resulting multidimensional schema is displayed in Figure 2. Graphic notations are inspired by (Golfarelli et al., 1998).

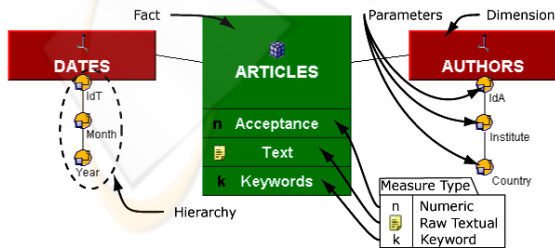


Figure 2: Example of a multidimensional conceptual schema for textual analysis.

## 2.2 Ontology and Operations

In order to allow analysis of textual measures, we use a hierarchical representation of domain concepts. These concepts are modelled through a “light” or “informal is-a” ontology (Lassila and McGuinness, 2001). It corresponds to a hierarchy of domain concepts where each node represent a concept (a keyword) and each link between nodes models a more complex relation than an “is-a” relation.

**Definition 4.** Given an ontology  $O$ , the *domain* of  $O$ , noted  $dom(O)$ , represents all the keywords of  $O$ .

For example in Figure 3,  $OLAP \in dom(O_{IS})$ .

**Definition 5.** We call *depth* of an ontology the maximum number of nodes between the root node and lowest nodes, i.e. the leaves.

In our example the  $depth(O_{IS}) = 8$ .

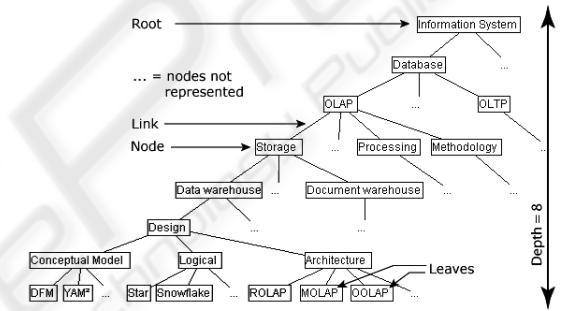


Figure 3: Example of a simple domain ontology on information systems named  $O_{IS}$ .

To allow the model to operate with the ontology, we provide two operations that take two nodes—keywords—as input:  $n_1$  and  $n_2$ .

**Definition 6.** The *Least Common Ancestor*:

$$lca : (dom(O))^2 \rightarrow dom(O)$$

$$(n_1, n_2) \mapsto n_{LCA}$$

is a function returning the least common ancestor ( $n_{LCA}$ ) within  $O$  between  $n_1$  and  $n_2$ .

**Definition 7.** The *Distance* between two nodes:

$$d : (dom(O))^2 \rightarrow \mathcal{N}$$

$$(n_1, n_2) \mapsto \max(d(n_1, lca(n_1, n_2)), d(n_2, lca(n_1, n_2)))$$

is a function that returns the number of nodes between the least common ancestor (LCA) and the lowest node.

In  $O_{IS}$ ,  $lca(ROLAP, Document Warehouse) = Storage$ . The distance between these two keywords is 4:  $d(ROLAP, Document Warehouse) = \max(d(ROLAP, Storage), d(Document Warehouse, Storage)) = \max(4, 1) = 4$ .

### 3 AGGREGATION FUNCTION

Multidimensional OLAP analysis on non-additive measures is very limited because actual systems provide only two aggregation functions: *COUNT* and *LIST* (Kimball, 1996). We redefine the *LIST* function in order to operate on a keyword measure.

**Definition 8.** *LIST* aggregation function:

$$LIST : X^n \rightarrow (dom(O))^n \quad \text{where}$$

$$(x_1, \dots, x_n) \mapsto (kw_1, \dots, kw_n)$$

$X = dom(kw) \times \mathbb{N}$   
generates the list of keywords without performing any aggregation and removes the keyword distance.

In this section we define the aggregation function for domain keyword measures.

#### 3.1 Keyword Aggregation Function

The aggregation function *AVG\_KW* is designed to aggregate sets of keywords. Given a set of keywords as input, the function generates a new set of aggregated keywords. The aggregation process uses the domain ontology defined in the conceptual model (ontology and document sources are supposed to be from the same domain). For each pair of keywords, the function finds the corresponding least common ancestor (LCA). But, when aggregating very distant keywords, no matter how deep the ontology is, there is a high probability of systematically returning the root keyword of the ontology. To avoid this, a limit within the aggregation process must be specified. Indeed, the further keywords are from one another, the more sense is lost during aggregation process. In order to overcome this problem, the function uses a maximum authorized distance when aggregating keywords:  $D_{MAX}$ . So far heuristics suggest a distance of 3 or 4 nodes and a domain ontology as deep as possible. So far, the ontology research field has not solved this problem.

To display results, we use a bi-dimensional table displaying a fact and two dimensions (Gyssens and Lakshmanan, 1997), (Ravat et al., 2006). For each combination of analysis axis values, the table contains a cell. *AVG\_KW* takes as input the content of these cells (sets of keywords) and produces a new set as output. The new set is composed of aggregated keywords and/or keywords from the original cell if aggregation failed due to excessive distances between the keywords.

**Definition 9.** We define the aggregation function:

$$AVG\_KW : X^n \rightarrow X^m \quad X =$$

$$(x_1, \dots, x_n) \mapsto (y_1, \dots, y_m), m \leq n$$

$dom(kw) \times \mathbb{N}$

**Input:**  $(x_1, \dots, x_n) \in X^n$  is an ordered set of keywords such that  $\forall x_i \in X, x_j \in X \mid i < j, d(x_i, x_{ROOT}) \leq d(x_j, x_{ROOT})$  (i.e. the furthest nodes from the root are first) and  $x_i = (kw_i, d_i)$  with  $kw_i \in dom(O)$  and  $d_i \leq D_{MAX}$ .

**Output:**  $(y_1, \dots, y_m) \in X^m$  is a set of aggregated keywords.

Output is generated using the following function:

**Definition 10.**

$$(x_i, x_j) \mapsto \begin{cases} x_{LCA} = (kw_{LCA}, l(x_i, x_j)) & \text{if } l(x_i, x_j) \leq D_{MAX} \\ (x_i, x_j) & \text{otherwise} \end{cases}$$

where:

$$l(x_i, x_j) = d(kw_i, kw_j) + d_i + d_j$$

$$kw_{LCA} = LCA(kw_i, kw_j)$$

If  $x_i$  and  $x_j$  are aggregated into  $x_{LCA}$  then  $x_i$  and  $x_j$  are removed from the input set  $X$  and  $x_{LCA}$  is added to  $X$ . The aggregation process is iterated on  $X$  until no more aggregation may be performed:

$$\forall (x_i, x_j) \in X^2, \nexists x_{LCA} \mid l(x_i, x_j) \leq D_{MAX}$$

Notice that for a given  $y_k$  of  $X$ , if  $d_k = 0$ , then the corresponding keyword  $kw_k$  was not aggregated during the process and  $\exists x_i \in X \mid x_i = y_k$ . Notice also that if  $\forall x_i, x_j \in X, l(x_i, x_j) > D_{MAX}$ , then there is no aggregation possible and  $(y_1, \dots, y_m) = (x_1, \dots, x_n)$  with  $m = n$ .

#### 3.2 Algorithm

The algorithm takes as input a list of keywords to be aggregated:  $KW\_LIST = \{kw_1, kw_2, \dots, kw_n\}$  and an ontology  $O$ . It produces as output an aggregated keyword list:  $Output\_List$ .  $d(keyword_1, keyword_2)$  is function that computes the distance between both keywords.  $Order\_List$  is a function that orders a list of keywords such that  $d(kw_i, kw_{ROOT}) \leq d(kw_j, kw_{ROOT})$ . That is, keywords are ordered by the level they may be found in  $O$ , starting by the lowest levels, i.e. the keywords furthest from the root.  $LCA$  is a function finding the least common ancestor of a pair of nodes in a tree. See (Harel and Tarjan, 1984) and more recently (Bender and Farach-Colton, 2000) for discussion and implementation of the LCA problem.

$\{KW\_List = OrderList(KW\_List, O);$



```

For each KWi of KW_List Do
  li = 0;
  For each KWj of KW_List, (j>i) Do
    KWLCA=LCA(KWi, KWj) ;
    lLCA=MAX(d(KWi, KWLCA), d(KWj, KWLCA))+1;
    If ( lLCA ≤ DMAX ) Then
      KW_List=KW_List-{KWi, KWj};
      KWi=KWLCA; li=lLCA;
    end_If;
  end_For;
  Add KWi to Output_List;
end_For;
    
```

### 3.3 AVG\_KW Example

The use of drilling operations makes intensive use of aggregations. Thus, for this example, we shall use the Roll-Up operation presented in introduction and the conceptual schema displayed in Figure 2. Table 1 presents a sample dataset of three documents. Two keywords have been extracted from each document.

Table 1: A sample dataset of three documents.

Documents	Keywords	Date	Author
Doc_1	Document Warehouse Algebra	Nov. 2004	Au_1
Doc_2	Data Warehouse Conceptual Model	Sept. 2004	Au_1
Doc_3	Logical Fact Table	Sept. 2004	Au_1

In Figure 4, the positions of the different keywords of the previous table are pointed out by rectangles in the ontology. Arrows show possible aggregation process (with distances between nodes specified). Here,  $D_{MAX}=3$ .

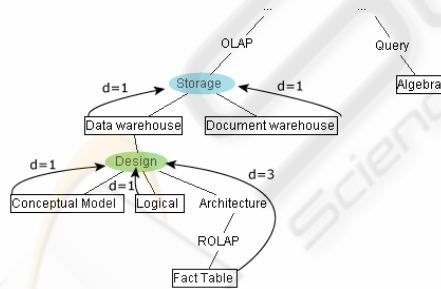


Figure 4: The position of the different keywords in the domain ontology  $O_{IS}$  (only partly represented).

In Figure 5-(a), the decision-maker analyses the publications of author  $Au_1$  during 2004 displaying results by *months*. The keywords of the two publications in September are aggregated: *Fact Table*, *Conceptual Model* and *Logical* are aggregated into *Design* with a distance of 3. *Data Warehouse* is too far away from the lowest keyword of the set that generated *Design*, thus it is not aggregated:  $d(\text{Fact Table}, \text{Data Warehouse}) = 4 > D_{MAX}$ .

In the document from November, the keyword *Algebra* is also too far from *Document Warehouse*, thus they are not aggregated either.

In Figure 5-(b), to get a more general view, the analyst “rolls-up” the analysis to a more general level of detail. Instead of observing results by *months* he will analyse them by *year*. Thus the system aggregates the two sets of keywords of the table (a) into a unique set in table (b). The keyword *Data Warehouse* has a distance of 1 with *Document Warehouse* and thus will be aggregated into *Storage* but *Design* has already a distance of 3 ( $D_{MAX}$ ), thus, as *Algebra* these keywords are too far and are not aggregated. The resulting cell in the mTable is:  $AVG\_KW((\text{Data Warehouse}, 0), (\text{Design}, 3), (\text{Document Warehouse}, 0), (\text{Algebra}, 0)) = ((\text{Storage}, 1), (\text{Design}, 3), (\text{Algebra}, 0))$ .

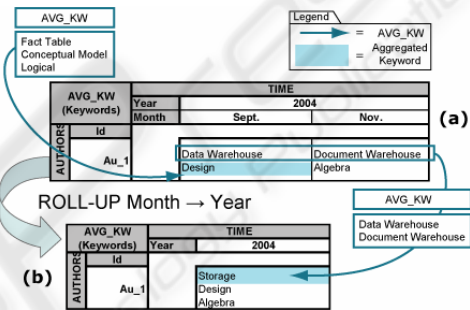


Figure 5: Analysis of keywords by months (a) and Roll-Up operation from TIME.Month to TIME.Year (b).

## 4 CONCLUSION

Up to now, OLAP systems are based on quantitative analysis with the use of numeric measures. As a first step towards multidimensional OLAP textual analysis, we presented in this paper a framework for the use of textual measures. In order to focus the analysis on textual data, textual measures were added to traditional multidimensional modelling. These measures allow the specification of elaborated textual measures such as keyword. We provide an aggregation function used during operations of the analysis process (such as drilling operations). This aggregation function aggregates keywords into more general ones with the use of a light domain ontology.

We are currently implementing our approach on top of an existing OLAP analysis tool: Graphic OlapSQL. This tool is based on a ROLAP data warehouse held in an Oracle *10g* RDBMS. The tool is a Java 5 client composed of a hundred classes.

We intend to continue our researches on several fields. The use of a light ontology (hierarchy of

concepts) as a domain ontology is simplistic. The idea would be to use an ontology with greater expressive power to be closer to domain semantics and concepts. Thus further studies should be conducted on the desirable ontology characteristics. Most end-user reporting tools display results with a tabular display such as the one used in this paper. This graphic interface is far from being adapted to display loads of keywords or textual data. Future efforts should also be oriented on a new display with a greater expressive power. Finally, keyword measures are part of a greater family of textual measures: *elaborated textual measures*, we intend to focus on a more general framework for all types of textual measures.

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