A Dimension Integration Method for a Heterogeneous Data Warehouse Environment

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Keywords: Multidimensional Schema Matching, Dimension Merging.

Abstract: Data Warehousing is the main Business Intelligence instruments that allows the extraction of relevant, aggregated information from the operational data, in order to support the decision making process inside complex organizations. Following recent trends in Data Warehousing, companies realized that there is a great potential in combining their information repositories in order to offer all participants a broader view of the economical market. Unfortunately, even though Data Warehouse integration has been defined from a theoretical point of view, until now no complete, widely used methodology has been proposed to support Data Warehouse integration. This paper proposes a method that is able to achieve both *schema* and *instance* level integration of heterogeneous Data Warehouse dimensions attributes by exploiting the topology of dimensions and the *dimension-chase* procedure.

1 INTRODUCTION

During the last two decades, Data Warehousing (DW) has been the main Business Intelligence (BI) instrument for the analysis of large banks of operational data. It allows managers to take strategic decisions based on aggregated information synthesized from the operational data.

In recent years, however, managers realized that new opportunities can be obtained from the Data Warehouse by combining information coming from more than one company, allowing them to have a broader view of the economical market. For example, it is common nowadays for two or more companies to merge, or to collaborate in a *federation-like* environment. In both cases, the Data Warehouses of the independent companies have to be combined in order to provide an unified view over the entire available information. The widest used approach, is to extract data from the repositories of all the participants through complex Extract-Transform-Load (ETL) processes, and then to rebuild the DW from the unified data repository. Apart from being a complicated approach due to the heterogeneity of the data repositories, this solution involves an enormous amount of work and it usually has high costs and long development times.

This approach may be considered a *low-end* solution, as the actual *integration* is being made at the early stages of the Data Warehouse building procedure. A more elegant solution would be to make a *high-end* integration of the DWs. Although this approach may seem less time and resource consuming, it presents nevertheless several difficulties, mainly deriving from the heterogeneity of the information and from the fact that the information to integrate is multidimensional.

In this paper we present a method for DW integration, that is able to (1) generate a set of consistent mappings between heterogeneous DW dimension levels, (2) import remote compatible dimensional attributes in a local schema and (3) populate the newly imported attributes with consistent information from the remote dimensional attribute.

The rest of this paper is organized as follows: Section 2 provides an overview on related work; Section 3 describes a technique to generate mapping predicates between heterogeneous DW dimension levels, while Section 4 describes the schema importation procedure. Finally, Section 5 draws the conclusions and provides an overview on possible future work.

2 RELATED WORK

Until now there have been few formalization attempts to solve the DW integration problem, and to the

Olaru M. and Vincini M..
A Dimension Integration Method for a Heterogeneous Data Warehouse Environment.
DOI: 10.5220/0004071702780283
In *Proceedings of the International Conference on Data Communication Networking, e-Business and Optical Communication Systems* (ICE-B-2012), pages 278-283
ISBN: 978-989-8565-23-5

knowledge of the authors, no complete methodology for the *high-end* DW integration has been proposed.

Some papers formalize, in some extent, the concept of similar multidimensional schemas. For example, (Golfarelli et al., 1998) defines the concept of *compatible schemas* and provides a method for computing the *overlap* of two DFM schemas, while (Cabibbo and Torlone, 2004) defines a *Dimension Algebra* (DA) that is then used to formalize the *intersection* of *compatible* dimensions. Although the DA can be used to formalize the solution for dimension integration, the paper doesn't provide a methodology for computing the DA expressions that can be used for integration purposes.

The work presented in (Banek et al., 2008) proposes a *linguistic* and *structure based* similarity function for multidimensional structures. The proposed method is inspired from classical data integration approaches (like (Beneventano et al., 2003; Madhavan et al., 2001; Melnik et al., 2002)), where designers make use of *affinity* functions to express similarities between *attributes* and *classes*. Although a similar approach may be used for the integration of heterogeneous DWs, we believe that the particular properties of the multidimensional structures that characterize the DWs can yield better results.

Am innovative architecture for the integration of heterogeneous DWs is proposed in (Golfarelli et al., 2010; Golfarelli et al., 2011), where the authors present the concept of *Business Intelligence Network* which is a peer-to-peer like network of DWs. The authors make use of mapping predicates to express similarity among concepts; unfortunately no *automatic* procedure for identifying the mapping predicates is provided.

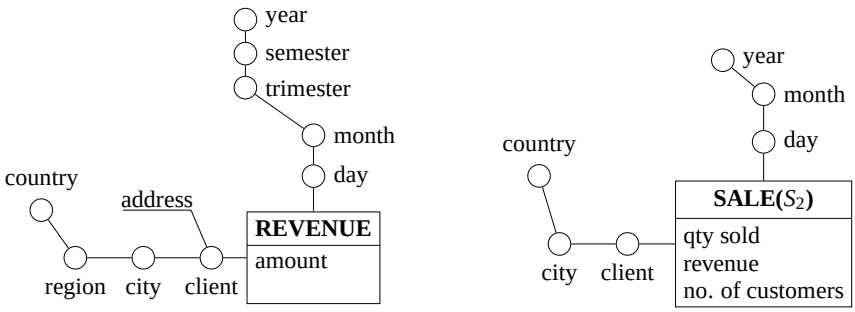
3 DIMENSION MAPPING STRATEGY

The first step of the method is to find similar dimension levels inside two dimension hierarchies. For this purpose, one may use classical data-integration approaches, like semantics or similarity measurement functions (see (Calvanese et al., 2001) for an example). However, even if in such a way it is possible to find semantically similar elements, we believe that such approach will not be able to provide the required accuracy in a multidimensional environment. The main reason is that two similar, but different dimensions, may contain related information (like a *time* hierarchy), but structured differently. This may lead to inconsistent analysis capabilities. Consider, for example, the dimensions in Figure 1. Suppose the first schema (call it S_1) contains the *REVENUE* fact table of a Data Warehouse (call it DW_1), and that the second schema (S_2) contains the *SALE* fact schema from another Data Warehouse (call it DW_2). Suppose that the goal is to integrate the information coming from the two DWs, and that managers have to be able to query them contemporaneously and to obtain an unified answer. In some cases, this is straightforward, in other cases it may raise some issues. For example, the total revenue divided by *city* and *month* may be obtained by combining the revenue from every individual DW, divided by *city* and *month*. Note that this query is possible because the required information is available in both DWs, at the required granularity. The only extra required information is that the dimension level $S_1.city$ is *equivalent* to the dimensional level $S_2.city$, and that the same may be said for the dimensional level *month*.

3.1 Equivalent Nodes Detection

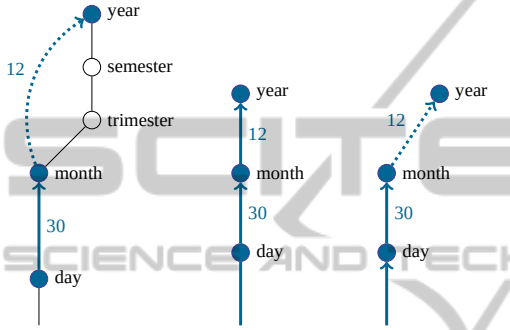
In order to automatically detect pairs of *equivalent* dimension levels, the method we propose makes use of the topology of dimensions. In fact, dimensions usually maintain a *tree-like* structure imposed by the partial order relationship on the dimensional attributes set. This property is maintained when dimensions represent a concept of the real world with a common structure. Consider, for example, that the time dimension of the instance of S_1 contains all the *days* from January 1st 2007 to December 31st 2010 (4 complete years), and that the time dimension of the schema S_2 contains all the *days* from January 1st 2009 to December 31st 2011 (3 complete years). Although the sets of the values of the attributes are only partially overlapped, this information may not be sufficient to discover semantic equivalences.

The method proposed in this paper relies instead on another property of dimension hierarchies, that we call *cardinality-ratio*. The *cardinality-ratio* is simply the ratio among the number of different elements between two dimension hierarchy levels. For example, in the *time* dimension in schema S_1, every element of the *month* level is an aggregation of approximately 30 different elements of the *day* level. Although it covers a different time period, the same property can be observed in the second *time* dimension. This information is maintained not only between directly connected dimension hierarchies. For example, in the schema S_2 a *year* is an aggregation of 12 different *months*. In schema S_1, a *year* is composed of 2 *semesters*, every *semester* is composed of 2 *trimesters*, where each *trimester* is composed of 3 different *months*. This means that a *year* is an ag-



(a) S_1 schema. (b) S_2 schema.

Figure 1: Example.



(a) First graph. (b) Second graph. (c) Common subgraph.

Figure 2: Dimension graphs.

gregation of $2 \times 2 \times 3$ different months, which is the same information that is directly available in the other hierarchy.

This property may be used not only on time dimensions, but on all dimensions that represent a concept of the real world with a fixed structure. For example, the geographical distribution inside one country is likely to be similar among all DWs that contain that particular geographical distribution. An address refers to a city, a city refers to a region, a region refers to a country.

In order to identify similar dimensional attributes, we first consider the dimension hierarchies as directed labeled graphs, where the dimension hierarchy levels are the nodes of the graphs and the label of each edge is the cardinality-ratio among different elements. Figure 2(a) is a directed labeled graph that represents the *time* dimension of the first schema (S_1), while Figure 2(b) represents the dimension of the second schema (S_2). Starting from these two graphs, it is possible to compute a common subgraph (Figure 2(c)) that can be used to identify pairs of equivalent nodes in the initial graphs.

The common sub-graph may be obtained from the first graph by eliminating the nodes *trimester* and *semester*, and by adding the directed edge $(month, year)$ (represented as dotted in Figure 2(a)). The common sub-graph is then used to map elements of the initial graphs. For example, the node *day* of the common subgraph is obtained from the node *day* of the first graph, or from the node with the same name of the second graph. This implies that nodes $S_1.day$ is *equivalent* to node $S_2.day$. Following the same approach, $S_1.month$ is *equivalent* to $S_2.month$ and $S_1.year$ is *equivalent* to $S_2.year$.

3.2 Mapping Set Generation

In order to express the complex relationships among various dimension levels, we make use of a subset of the mapping predicates proposed in (Golfarelli et al., 2010), in particular:

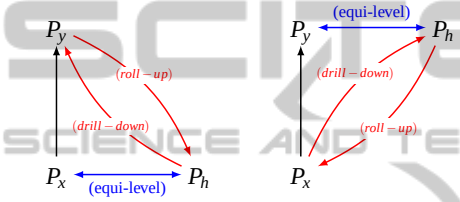
- **Equi-level Predicate:** used to state that two attributes in two different md-schemas have the same granularity and meaning;
- **Roll-up Predicate:** used to indicate that an attribute (or set of attributes) of the first md-schema aggregates an attribute (or set of attributes) of the second md-schema;
- **Drill-down Predicate:** used to indicate that an attribute (or set of attributes) of the first md-schema disaggregates an attribute (or set of attributes) of the second md-schema;
- **Related Predicate:** indicates that between two attributes there is a $many-to-many$ relation;

To generate the complete mapping set, we make use of the following inference rules:

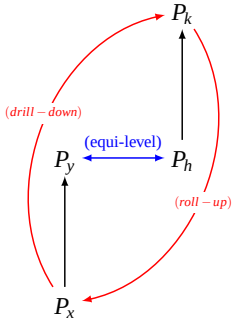
Let P_x and P_y be two nodes of the first graph such that there is a path from P_x to P_y, and P_h and P_k two nodes of the second graph such that there is a path from P_h and P_k

1. **Rule 1:** If P_x and P_h are equivalent, add the mapping:
   * $P_x\ (equi-level)\ P_h$

2. **Rule 2:** if P_x $(equi-level)$ P_h, add the mappings:
   * P_y $(roll-up)$ P_h
   * P_h $(drill-down)$ P_y (See Figure 3(a))
3. **Rule 3:** if P_y $(equi-level)$ P_h, add the mappings:
   * P_x $(drill-down)$ P_h
   * P_h $(roll-down)$ P_x (See Figure 3(b))
4. **Rule 4:** if P_y $(equi-level)$ P_h, add the mappings:
   * P_x $(drill-down)$ P_k
   * P_k $(roll-up)$ P_x (See Figure 3(c))
5. **Rule 5:** for every nodes P_x and P_h of the two graphs for which there has not been found any mapping rule, add the mapping:
   * P_x $(related)$ P_h



(a) Rule 2. (b) Rule 3.



(c) Rule 4.

Figure 3: Graphical representation of rules 2, 3 and 4.

4 DIMENSION MERGING

The mappings discovered in Section 3 can be used to formulate queries on a set of compatible Data Warehouses, using query rewriting techniques. A major drawback of this approach is that the query rewriting accuracy depends on the compatibility of the schemas. For example, considering the schemas in Figure 1, a possible query would be to obtain the total revenue divided by city and month. This query is compatible, as the required information is available in both Data Warehouses, at the required level of aggregation. However, other queries are incompatible. For example, on the schema S_1 it is possible to execute a query to obtain the total revenue, divided by *region* and *month*. In this case however, the query would return only information coming from DW_1, as the expressed query cannot be formulated on DW_2.

One way of bypassing this problem is to uniform the analysis capabilities of the peers, by making the dimensions as similar as possible. This may be achieved, for example, by importing, where possible, compatible parts of remote DW dimensions.

4.1 Partial Schema Importation

The presence of at least one <*equi-level*> mapping suggests that the two dimensions have common information, so their schemas are overlapped, as defined in (Golfarelli et al., 1998). The key idea is to use that common schema information as a starting point for importing other dimensional attributes. The attributes are first inserted as optional attributes, and then, if sufficient information is available in the two DWs, the attributes are modified to mandatory attributes.

For example, consider that by exploiting the method proposed in Section 3, we obtain the following mappings:

- $\omega_1 : S_1.city$ <equi-level>$S_2.city$ (Rule 1).
- $\omega_2 : S_1.country$ <equi-level>$S_2.country$ (Rule 1).
- $\omega_3 : S_1.region$ <roll-up>$S_2.city$ (Rule 2).
- $\omega_4 : S_1.region$ <drill-down>$S_2.country$ (Rule 3).

If it were possible to *import* the *region* attribute inside the schema S_2, then queries involving the geographical hierarchy may be expressed on both DWs, with the same query answering capabilities. The integration, however, must be done at both schema and instance level.

To formalize this step, we decided to use *Dimensional Fact Model* (Golfarelli et al., 1998), mainly because this particular model defines the concept of *optional* dimensional attribute. The DFM describes a fact schema as a sextuple $f = (M, A, N, R, O, S)$, where:

- M is a set of *measures* defined by a numeric or Boolean value.
- A is a set of *dimensional attributes*.
- N is a set of *non-dimensional attributes*.
- R is a set of ordered couples that define the $quasi-tree$ representing the dimension hierarchy.
- $O \subseteq R$ is a set of $optional$ relationships.
- S is a set of aggregation statements.

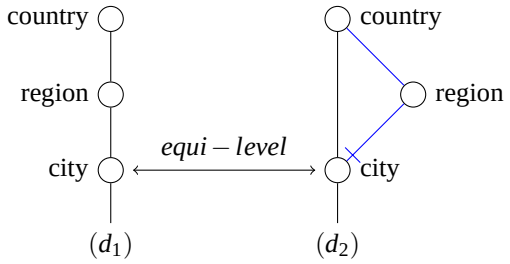


Figure 4: Graphical example of the importation rule.

The first step of the schema importation procedure is based on the following rule:

Rule 1. *Given two fact schemas* $f_1 = (M', A', N', R', O', S')$ *and* $f_2 = (M'', A'', N'', R'', O'', S'')$*, and the set* $\mathcal{M}$ *of mappings between the two schemas, let* $a'_i, a''_i \in A'$ *such that* $(a'_i, a''_i) \in R'$*, and* $a'_j \in A''$*. If* $\{(a'_i < equi-level > a'_j), (a''_i < roll-up > a'_j)\} \subseteq \mathcal{M}$*, then:*

$$A'' := A'' \cup \{a''_i\} \quad (1)$$
$$O'' := O'' \cup \{(a'_j, a''_i)\}$$

If $\exists\ a''_j \in A''$ *such that* $\{(a'_j, a''_j)\} \subseteq R''$*, and* $\{(a''_i < drill-down > a''_j)\} \subseteq \mathcal{M}$*, then:*

$$R'' := R'' \cup \{(a''_i, a''_j)\} \quad (2)$$

Figure 4 contains a graphical example of the importation Rule. Dimensions d_1 and d_2 are the corresponding dimensions of DW_1 and DW_2 as defined in Figure 1. As $region, city \in A'$ and $(city, region) \in R'$ and $city \in A''$, and $(S_1.region < roll-up > S_2.city)$, then, according to (1), the attribute *region* is inserted among the attributes of S_2 and the ordered tuple $(city, region)$ is inserted in O''. Then, for every dimensional attribute in A'' that is a $roll-up$ of the newly inserted attribute, an ordered couple is added to R'', in order to express the given semantic relation. As $S_2.country < roll-up > S_1.region$, the ordered couple $(region, country)$ is inserted in R''.

4.2 Data Importation

In order to import information from remote dimensions, the *dimension-chase* (Torlone, 2008) (or *d-chase*) algorithm is used. The *d-chase* procedure is a derivation of the *chase* algorithm presented in (Abiteboul et al., 1995) for reasoning on dependencies in relational databases. The procedure consists in creating an initial *tableau* from the dimensions and applying a *chase step* recursively until the completion of the tableau.

With a little abuse of notation, the information contained in the two dimensions will be represented as a table. Table 1 represents the initial tableau, built by adding all the attributes of the two dimensions (the couples of attributes in the two dimensions that are connected by an $< equi-level >$ relation are inserted only once, as they represent the same concept). The tuples in the table are the tuples of the dimensions. For every column representing an attribute not contained in the dimension, the value is replaced by a variable (see last three rows). Suppose that the first three rows represent the information contained in the first dimensions (d_1), while the last three rows represent the information from the second dimension (d_2). The *chase-step* consists in recursively applying the following rule:

Rule 2. $\forall a_1, a_2 \in A'$ *such that* $(a_1, a_2) \in R'$*, or* $a_1, a_2 \in A''$ *such that* $(a_1, a_2) \in R''$*, if* $\exists\ t_1, t_2 \in T$ *such that* $t_1[a_1] = t_2[a_1]$ *and* $t_1[a_2] \neq t_2[a_2]$*, then if* $t_1[a_2]$ *is a variable, assign it the value* $t_1[a_2] := t_2[a_2]$ *(vice-versa if* $t_2[a_2]$ *is a variable).*

The chase ends after no possible assignment can be made using the information available in the tableau. In the given example, the procedure successfully assigns v_1 the value "ER" and to v_2 the value "TO". However, no value is assigned to variable v_3, because no sufficient information is contained in the first dimension. The final tableau can be used to import the required information in the second dimension. First of all, the tableau needs to be projected on the final schema of the dimension in which to import the information (d_2 in the example), in order to import the values of the dimension levels of interest. There are two aspects of the information importation step. First of all, the newly inserted dimensional attribute (*region*) is populated with compatible values found in the other dimension. Secondly, the importation step increases the information previously available in the initial dimension, due to the possibility of importing the tuples from the tableau originated from the remote dimension (d_1 in our case).

As stated earlier, if sufficient information is contained in the two dimensions, then the attribute originally inserted (*region*) can be *promoted* to a normal attribute. This is possible only if the values of the newly inserted attribute have all been populated. Using the tableau, this is true only if all variables in the column have been assigned a value from the other dimension. This is not the case in our example, as variable v_3 has been assigned no value after the execution of the *d-chase* algorithm.

Table 1: Tableau.

client	city	region	country	dimension
M.ROSSI	MODENA	ER	ITALY	d1
P.BIANCHI	FLORENCE	TO	ITALY	d1
A.RENZO	BOLOGNA	ER	ITALY	d1
A.MANCINO	MODENA	*v*1	ITALY	d2
S.RUSSO	FLORENCE	*v*2	ITALY	d2
T.CONTI	ROME	*v*3	ITALY	d2

5 CONCLUSIONS

The work presented in this paper describes a method for the integration of heterogeneous Data Warehouse dimensions. The main conclusion that can be drawn from the paper is that the particular multidimensional structure of DW information may be successfully exploited together with other classical data integration approaches/techniques (like the d-chase procedure) to achieve DW integration.

The method proposed in the paper is divided into two steps. First, topological properties are used to generate a mapping set between various dimension levels, then, compatible schema parts, and the information that is populated by, are integrated. The steps can be independently modified in order to increase the accuracy. In fact, one area of possible future work is to expand the mapping generating step by using a mixture of approaches, for example by adding the use of semantics. It has been proven in classical data-integration (for example (Bergamaschi et al., 2007)) that a combined approach usually increases the accuracy of the mapping generation step.

Another challenging problem in DW integration that we believe will be the fruit of intensive research is the final integration of multidimensional information. Although it relies on mapping predicates, this particular step will raise some issues, like the discovery of common information which needs to be identified in order to maintain the final result unaltered.

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