A FRAMEWORK FOR QUALITY EVALUATION IN DATA INTEGRATION SYSTEMS

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Abstract: Ensuring and maximizing the quality and integrity of information is a crucial process for today enterprise information systems (EIS). It requires a clear understanding of the interdependencies between the dimensions characterizing quality of data *(QoD)*, quality of conceptual data model *(QoM)* of the database, keystone of the EIS, and quality of data management and integration processes *(QoP)*. The improvement of one quality dimension (such as *data accuracy* or *model expressiveness*) may have negative consequences on other quality dimensions (e.g., *freshness or completeness of data).* In this paper we briefly present a framework, called QUADRIS, relevant for adopting a quality improvement strategy on one or many dimensions of *QoD* or *QoM* with considering the collateral effects on the other interdependent quality dimensions. We also present the scenarios of our ongoing validations on a CRM EIS.

1 INTRODUCTION

More and more systems need to integrate data coming from multiple and heterogeneous data sources and provide the users with a uniform access to data. These systems, called data integration systems *(DIS)* can be of several kinds, such as mediation systems or data warehousing systems. Mediation systems offer a uniform access to multiple data sources; user queries are split and directed towards various data sources through wrappers, and the results returned by the sources are combined by a mediator and sent to the users. Data warehousing systems aim at providing integrated information for decision-making; they materialize the information extracted, transformed, and cleaned from several data sources, possibly web-based sources in a data webhousing context.

Ensuring the quality of data is an important problem which conditions the success of most existing information systems in enterprises. If ignored, data quality may have a considerably negative impact on the success of the enterprise. In the case of *DISs*, the problem is particularly difficult due to the integration of data coming from multiple sources that have various schemata, various levels of quality and trust, and autonomous evolution and administration. Maintaining traceability, freshness, non-duplication and consistency of very large data volumes for integration and decision-making purposes is thus one of the major scientific and technological challenges today.

In this short paper, we claim that data quality in enterprise information system *(EIS)* cannot be restricted to one-shot approaches addressing separately simpler or more abstract versions of the problems when data is incomplete, inaccurate, inconsistent, imprecise, uncertain, duplicated or staled. Quality is multidimensional and has to be addressed at three levels of the EIS design: the quality of the conceptual data model *(QoM)*, the quality of stored data *(QoD)*, and the quality of processes on data *(QoP)*. We propose a framework, called QUADRIS that studies the interdependencies between the various dimensions of quality at each level of the EIS design and also between the levels.

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The framework is developed within a project of the same name, grouping four academic research teams and two industrial users. The project is supported by the French National Agency for Research.

The rest of the paper is organized as follows: Section 2 gives an illustrative example of an EIS for customer relationship management showing the issue of quality in this application context. Section 3 presents the QUADRIS framework with the definition of quality dimensions and metrics we consider. Section 4 presents QUADRIS' proofs of concept, based on the assumptions that are currently under validation on realistic and operational data sets in one of three application domains we consider: CRM data from the French Electrical Company *EDF*, medical data from *Institut Curie*, and geographical flooding data from *Cemagref*.

2 ILLUSTRATIVE EXAMPLE IN A CRM APPLICATION

Customer Relationship Management (CRM) is a process used to learn more about customers' needs and behaviors in order to develop stronger relationships with them and to identify, acquire, foster and retain *loyal and profitable customers*. From a functional point-of-view, Figure 1 depicts a generic and simplified architecture of the EIS for a CRM application that integrates data coming from 3 sources (*S1, S2, S3*) with their respective data model (*M1, M2, M3*), by means of 6 integration processes (e.g., ETL, cleaning) working on input/output information flows (*f1*, …, *f13*), and the CRM database *CRM_DB*. Since engineering and integration processes and human expert can introduce errors, quality control (QC) procedures which can prevent and detect errors on data models, on processes or on data become important components of the global system. Consequently QC policies over data models, databases, data flows and processes operating on data (e.g., *QC[M1], QC[f5], QC[CRM_DB]*, etc.) may be designed at each level for evaluating and improving the quality of the data models (*QoM*), the quality of processes (*QoP*), and the quality of data (*QoD*). In the last case, they can be used to detect and correct data quality problems of completeness (*i.e.,* missing values), freshness, uniqueness (*i.e.,* presence of duplicates), and valuation errors (e.g., misspellings, outliers, inconsistencies, contradictions, constraints violations, etc.).

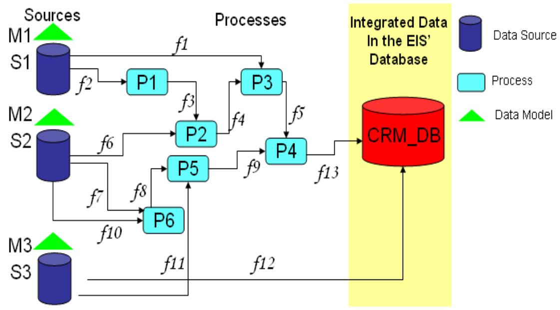

Figure 1: Data integration in the CRM database of the back-office EIS.

Each QC policy for *QoD* may combine several techniques (such as ETL, exploratory data mining, data sampling and tracking, etc.) for error detection and correction. For CRM data integration, several pieces of information (with potential overlaps or conflicts) that describe the customer may come from various sources through different paths (and processes). Setting up systematically QCs for each data flow, data model or process of the global system is unaffordable and impossible in practice. It is thus necessary to determine quality hot-spots and vulnerabilities in the system (*i.e.,* data flows, processes or models that generate and propagate data quality problems) in order to: *i)* choose the ``best'' path (less likely exposed to data quality problems) and *ii)* target preventive or corrective actions depending on the costs they generate at the different levels, from the first steps of EIS design and engineering (*i.e.*, at the data model level), to the management and integration of data (at the data and process levels) (Peralta 2006).

3 QUADRIS FRAMEWORK

Before introducing our vision of quality in the QUADRIS project, we clarify the terminology used in the rest of the paper. Our quality approach is based on a meta-model (Vassiliadis+ 2000), whose main concepts are represented in the schema of Figure 2 and defined hereafter. We argue that the quality of an information system may be defined according to several *views*, for instance the specification, usage and implementation views (Sisaïd+2002). The specification view is related to the specification aspects and measures the quality of the models. The implementation view refers to the implementation aspects both for data and processes. The usage view defines the user perceived quality of the final system.

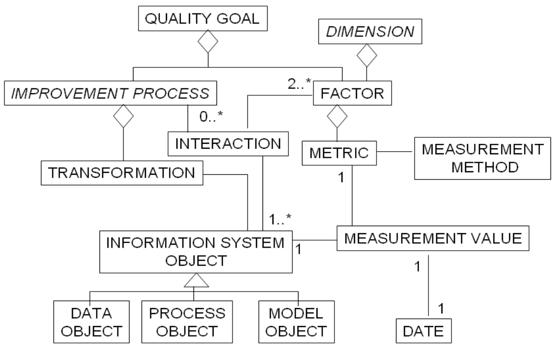

Figure 2: Meta-model for evaluating and improving quality.

A quality of an information system is measured through a set of quality *dimensions* (Vassiliadis 2000). A quality dimension describes a quality characteristic the information system has to meet. Some of these dimensions are detailed below (freshness, completeness, etc.). Each quality dimension could be measured applying either a *formal or an informal measurement* method. A formal measurement method could be a metric or an expression. An informal measurement method could be a range of scores or a qualitative opinion assigned by a user or a designer. Our measurement of quality is motivated by the need to propose *corrective rules* aiming to improve the IS quality value. These rules could be *restructuring rules* applied on the IS models, corrective actions applied on data or redefinition actions applied on processes (Peralta 2006). The quality measurement on the information system (*data, models* and *processes*) enables the designer to compute a set of IS quality indicators that are used by the transformation rules (Sisaïd+2006).

3.1 Quality of Data

Quality of data (*QoD*) is a multidimensional, complex, morphing and goal-oriented concept (Dasu+ 2003). This notion includes the following dimensions:

Data Completeness concerns the degree to which all data relevant to an application domain has been recorded in an information system (Gertz+2004). It expresses that every fact of the real world is represented in the information system (Bobrowski+1998). Two different aspects of completeness can be considered: *(i) Coverage* (Naumann+2003) describes whether all required entities for an entity class are included; *(ii) Density* (Naumann+2003) describes whether all data values are present (not null) for required attributes.

Data Uniqueness states that two or more values do not conflict each other (Mecella+2002).

Data Consistency expresses the degree to which a set of data satisfies a set of integrity constraints (Redman 1996). Data is said consistent if it satisfies these constraints. The most common constraints checks for null values, key uniqueness and functional dependencies.

Data Freshness introduces the idea of how old is the data: Is it fresh enough with respect to the user expectations? Has a given data source the more recent data? Is the extracted data stale? When was data produced? There are two main freshness definitions in the literature: *(i) Currency* (Segev+1990) describes how stale is data with respect to the sources. It captures the gap between the extraction of data from the sources and its delivery to the users. For example, given an account balance, it may be important to know when it was obtained from the bank data source. *(ii) Timeliness* (Wang+1996) describes how old is data (since its creation/update at the sources). It captures the gap between data creation/update and data delivery. For example, given a top-ten CD list, it may be important to know when the list was created, no matter when it was extracted from sources. Data freshness evaluation has extensively been studied in (Bouzeghoub & Peralta 2004).

Data Accuracy is concerned with the correctness and precision with which real world data of interest to an application domain is represented in an information system (Gertz+2004) (Peralta 2006). It introduces the idea of how precise, valid and error-free is data: Is data in correspondence with real world? Is data error-free? Are data errors tolerable? Is data precise enough with respect to the user expectations? Is its level of detail adequate for the task on hand? There are three main accuracy definitions in the literature: *(i) Semantic correctness* (Wang+1996) describes how well data represent states of the real-world. It captures the gap (or the semantic distance) between data represented in the system and real-world data. For example, the recorded address "45, av. des États-Unis" is actually the address of Mike? *(ii) Syntactic correctness* (Naumann+1999) expresses the degree to which data is free of syntactic errors such as misspellings and format discordances. It captures the gap (or syntactic distance) between data representation in the system and expected data representation. For example, the address "45, av. des États-Unis" is valid and well-written? *(iii) Precision* (Redman 1996) concerns the level of detail of data representation. It captures the gap between the level of detail of data in the system and its expected level of detail. For example, the amount "$2008" is a more precise representation of the salary of John that "$2000".

3.2 Quality of Data Model

This section proposes some quality dimensions for data model quality measurement:

Completeness. A conceptual schema is complete when it represents all relevant features of the application domain (Batini et al., 1992). More specifically, the completeness can be measured by the degree of coverage of users' requirements by the conceptual schema. Completeness is a very important criterion as it is crucial for the success of the future system. In other words, the degree of disparity, between user requirements and their interpretation by the designer as expressed in the conceptual schema, measures the gap between the user's and the designer's perception of the same reality.

Understandability. Understandability is defined as the ease with which the user can interpret the schema. This criterion is very important for the validation phase and consequently influences directly the measure of completeness. The understandability of a conceptual schema relies on how much modeling features are made explicit. Non-explicit names, a high level of aggregation of the modeling features, and the complexity of the defined integrity constraints are factors that decrease the schema understanding.

Minimality. A schema is said to be minimal when every aspect of the requirements appears only once (Batini et al., 1992). In other words, non-minimality is due to a lack of factorization. A bad choice of entities and generalization hierarchies may lead to the replication of relationships in which several entities are involved playing the same role.

Expressiveness. A schema is said to be expressive when it represents users' requirements in a natural way. We distinguish between concept and schema expressiveness. Concept expressiveness measures whether the concepts are expressive enough to capture the main aspects of the reality. For example, an inheritance link is more expressive than a relationship in the EER model. Indeed, an inheritance link from entity-type E1 to entity-type E2 expresses the fact that: *i)* there exists a relationship between E1 and E2, *ii)* the set of E2 occurrences is included in the set of E1 occurrences, *iii)* E2 shares all properties of E1, *iv)* E2 participates to all relationship-types to which E1 participates. Thus we propose to associate weights with the different concepts involved. Schema expressiveness measures the expressiveness of the schema as a whole. It is clear that the greater the number of concepts used is the higher the expressiveness of the conceptual schema is.

4 EXPRESSING INTERDEPENDENCIES OF QUALITY DIMENSIONS

As reported in several recent studies, data quality problems cost hundreds of billions of dollars a year to the companies. Combined approaches should explore databases both at the extensional and intentional levels, quickly detect data quality problems (such as duplicates, contradictions, inconsistencies, stale or incomplete data), correct, evaluate, improve and ensure information quality of the enterprise information systems. For ensuring and maximizing the quality and integrity of information, a clear understanding of the interdependencies between the measurable dimensions characterizing quality of data, quality of data model, and quality of data management processes are needed, since the improvement of one dimension may not have as a consequence the improvement of the other *QoD* dimensions. Thus, adopting a quality improvement strategy for one or many dimensions of *QoD*, *QoM*, or *QoP* should take into account both its total cost and the collateral effects on the other interdependent *QoD* dimensions. The next subsections present our study in the QUADRIS framework related to this problem.

4.1 Impact of QoM on QoD

Consider that the data of the CRM EIS, noted *Ds* is stored in a database with a conceptual data model *Ms* for which each quality dimension, noted *i* ($i \in dimQoM$) defined in Section 2.2 is evaluated, as illustrated in Figure 3. Each data quality dimension *j* is also measured ($j \in dimQoD$). When the model is transformed into a new data model *Ms'*, the measures of the quality of this new model, *QoM(i,Ms')* and the ones of the quality of corresponding data, *QoD(j,Ds')* change respectively for each dimension.

The purpose of the QUADRIS meta-model is to identify and demonstrate which and how dimensions of *QoM* are correlated together with the dimensions

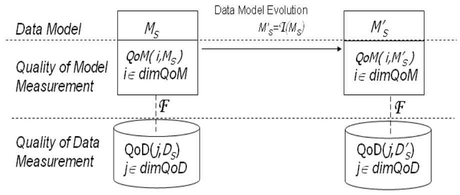

Figure 3: Interdependencies between *QoM* and *QoD* dimensions.

of *QoD*. Typically, an action on *QoM* dimensions may have positive or negative consequences on the measures of *QoD* dimensions: e.g., increasing the minimality of the conceptual data model of the EIS database may also decrease the completeness of data; increasing the expressiveness of the model by adding integrity constraints may also increase data uniqueness, data accuracy, and data consistency. Our study focuses on the quantification of such correlations represented in Figure 3 by the function $\mathcal{F}$. Orthogonally, we study the transformations $\mathcal{T}$ that can be made on the model *Ms* (e.g., adding constraints, checking assertions, or changing the schema) that are cost-optimal and preserve the positive effects of the function $\mathcal{F}$.

4.2 Interdependencies between QoD Dimensions

Analogously, we measure each dimension of data quality of the EIS database (*j, j' ∈ dimQoD*) and we

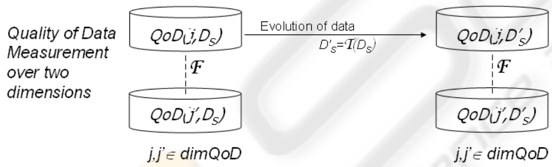

Figure 4: Interdependencies between *QoD* dimensions.

apply a transformation $\mathcal{T}$ on the dataset *Ds* that becomes *Ds'*. Such a transformation will have consequences on the quality measures of other *QoD* dimensions (*QoD(j',Ds')*). Again our framework intends to identify which of and how the considered *QoD* dimensions are correlated with the same function $\mathcal{F}$, as illustrated in Figure 4. For example, if we increase the accuracy of data to be integrated and loaded into the EIS database, this will require additional cross-checking procedures, and thus, it will decrease the freshness of data.

5 ONGOING VALIDATIONS ON CRM EIS

Intuitively presented in the previous subsections, our approach will be validated on operational data sets for the CRM application domain, provided by EDF. Quite similar approaches have been defined for the medical and geographical domains. All these domains are of course very concerned by the quality of their databases since a low quality of data could have considerably negative financial impacts and even lead to harmful decision. The EDF Group is an integrated energetic utility, and manages all aspects of the electricity business. Here, we focus on a commercial aspect of the group. EDF has a strong footing in Europe, with a total of 40.2 million customers worldwide (including 28 million in France). Thus, its CRM databases treat a large volume of multi-source information. The database chosen for QUADRIS framework validation is used for the management of major and small business French markets (these markets represent 2.3 million customers). This relational database is called *CRM_DB* in the following. This database is a crucial component of a complex chain of data integration processes (as in Figure 1). Two scenarios in close connection with the database quality have been defined. Their goal is to display quality requirements related to the use of *CRM_DB*. These scenarios start with an operational aim and they end with a precise definition of the metrics used to measure the quality dimensions concerned by this operational aim. This step is obviously crucial in order to understand which dimensions (and their corresponding metrics) of *QoM*, *QoD* and *QoP* affect *CRM_DB*.

Validation of the impact of QoM on QoD. In order to validate the impact of *QoM* on *QoD*, we consider two different conceptual data models of *CRM_DB: M* and *M'*. The *M'* model is the current version of *CRM_BD* conceptual model and *M* is the previous one. We inject the same information in *M* and *M'* so that the respective corresponding data *D* and *D'* are comparable. The approach has three steps:

1. Measurement of the conceptual data model quality dimensions for *M* and *M'* (w.r.t. dimensions defined in Section 2.2 and dimensions exhibited by the scenarios) with the appropriate metrics
2. Measurement of the data quality dimensions for *D* and *D'* (w.r.t. dimensions defined in Section 2.1 and dimensions exhibited by the scenarios) with the appropriate metrics

3. Comparison of results by couple of metrics *(i,j)* where *i* is a conceptual data model quality metric and *j* is a data quality metric.

Validation of interdependencies between QoD dimensions. In order to validate the interdependencies between *QoD* dimensions, we focus on one status of *CRM_DB*. Then, for each couple (d_1,d_2) of quality dimensions (Section 2.1, namely, freshness and accuracy, completeness and uniqueness, completeness and consistency), we use the following approach:

1. Measure of d_1 and d_2 for *CRM_DB*
2. Artificial deterioration (or improvement) of the data quality for the dimension d_1
3. Characterization of d_2 behavior.

6 CONCLUSIONS

This paper describes an ongoing research project dedicated to the evaluation and improvement of data quality in enterprise information systems. A framework, called QUADRIS, has been proposed and is currently under experimentations on very large databases in three application domains: CRM (*EDF*), medical domain (*Institut Curie*) and geographical domain (*Cemagref*). The aim is to identify the interdependencies between quality dimensions considering two IS design levels: *i)* interdependencies between dimensions of quality of data (*QoD*), and *ii)* interdependencies between *QoD* dimensions and quality of conceptual data model (*QoM*) dimensions. This study already offers very interesting and quantifiable perspectives for designing quality-aware information systems and for setting up cost optimal strategies for data quality prevention and improvement in EIS.

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