ELSEVIER

Decision Support Systems 13 (1995) 349–372

Decision Support Systems

Toward quality data: An attribute-based approach

Richard Y. Wang *, M.P. Reddy, Henry B. Kon

Massachusetts Institute of Technology, Cambridge, MA, USA

Abstract

A quality perspective in data resource management is critical. Because users have different criteria for determining the quality of data, we propose tagging data at the cell level with quality indicators, which are objective characteristics of the data and its manufacturing process. Based on these indicators, the user may assess the data's quality for the intended application. This paper investigates how such quality indicators may be specified, stored, retrieved, and processed. We propose an attribute-based data model, query algebra, and integrity rules that facilitate cell-level tagging as well as the processing of application data that is augmented with quality indicators. An ER-based data quality requirements analysis methodology is proposed for specification of the kinds of quality indicator to be modeled.

Keywords: Data quality; Requirements analysis; Data management; Metadata; Database design

1. Introduction

Organizations in industries such as banking, insurance, retail, consumer marketing, and health care are increasingly integrating their business processes across functional, product, and geographic lines. The integration of these business processes, in turn, accelerates demand for more effective application systems for product development, product delivery, and customer service [25]. As a result, many applications require access to corporate functional and product databases. Unfortunately, errors in databases have been measured in the ten percent range and higher for a variety of applications [12,16,22,24].

In general, inaccurate, out-of-date, or incomplete data can have significant impacts both socially and economically [16,17,29]. Managing data quality, however, is a complex task. Although it would be ideal to achieve *zero defect data*, this may not always be necessary or attainable for, among others, the following two reasons.

First, in many applications, it may not always be necessary to attain zero defect data. In the U.S., postal mail may be delivered correctly, even if the city-name is incorrect, as long as the zip code is correct. Similarly, data users who are familiar with the data can often detect or work around errors.

Second, there is a cost-quality tradeoff in implementing data quality programs. Ballou and Pazer found that "in an overwhelming majority of cases, the best solutions in terms of error rate

* Corresponding author.

reduction is the worst in terms of cost" [2]. The Pareto Principle suggests that losses are never uniformly distributed over the quality characteristics. Rather, losses are typically concentrated in a small percentage of the quality factors [13]. In sum, when the cost is prohibitively high, it is not economically feasible to attain zero-defect data.

Given that zero defect data may sometimes be neither necessary nor attainable, it would be useful to be able to *judge* the quality of data without having to do a full data inspection or regenerating the data anew. This suggests that we tag data with quality *indicators* which are *characteristics of the data and its manufacturing process*. From these quality indicators, the user can make a judgment of the quality of the data for the specific application at hand. In making a financial decision to purchase stocks, for example, it would be useful to know the quality of data through quality indicators such as the source of the data, when the data was collected, and how the data was collected.

In this paper, we propose an attribute-based model that facilitates the cell-level tagging of data. From these quality indicators, the user can make a better *interpretation* of the data and determine the *believability* of the data.

Included in this attribute-based model are an extension of the relational model, a set of quality integrity rules, and a quality indicator algebra which defines a relational processing of application data augmented with quality indicators. In order to determine what kinds of quality indicators are to be tagged to the data, an E-R based data quality requirements analysis methodology is also presented.

1.1. Dimensions of data quality

Just as it is difficult to manage product quality without understanding the attributes of the product which define its quality, it is also difficult to manage data quality without understanding the characteristics that define data quality. Therefore, before one can address issues involved in data quality, one must define what data quality means. In the following subsection, we present a definition for the dimensions of data quality.

Accuracy is the most obvious dimension when it comes to data quality. Morey suggested that "errors occur because of delays in processing times, lengthy correction times, and overly or insufficiently stringent data edits" [22]. In addition to defining *accuracy* as "the recorded value is in conformity with the actual value," Ballou and Pazer defined *timeliness* (the recorded value is not out of date), *completeness* (all values for a certain variables are recorded), and *consistency* (the representation of the data value is the same in all cases) as the key dimensions of data quality [2]. Huh et al. identified accuracy, completeness, consistency, and *currency* as the most important dimensions of data quality [11].

It is interesting to note that although methods for quality control have been well established in the manufacturing field e.g.,[13], neither the di-

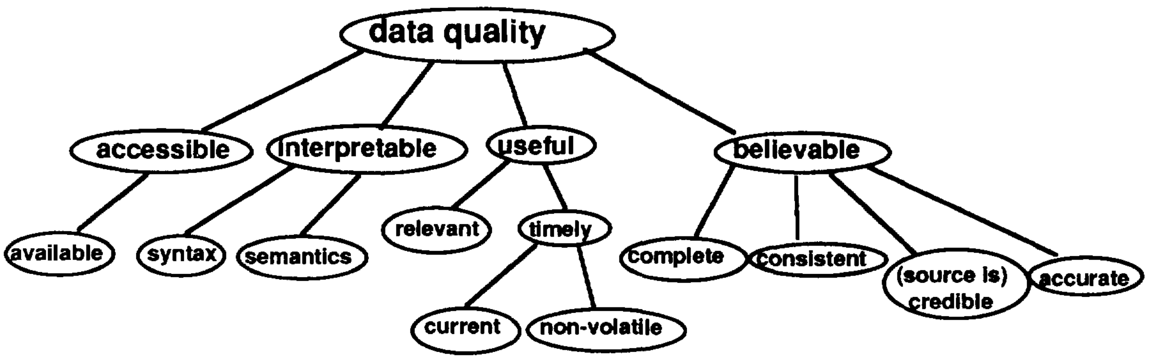


Fig. 1. A hierarchy of data quality dimensions.

mensions of quality for manufacturing nor for data have been rigorously defined [1,8,9,10,11,13, 22,31]. This may be due, in part, to the heterogeneity in general product characteristics.

Various data, however, even from disparate application domains, have common dimensions upon which its quality can be measured. Data quality is both a multi-dimensional and a hierarchical concept. Figure 1 depicts one possible representation of the dimensions of data quality, motivated by the following discussion.

First the user must be able to get to the data, which means that the data must be *accessible* (the user has the means and privilege to get the data). Second, the user must be able to *interpret* the data (the user understands the syntax and semantics of the data). Third, the data must be *useful* (data can be used as an input to the user's decision making process). Finally, the data must be *believable* to the user (to the extent that the user can use the data as a decision input). Resulting from this list are the following four dimensions: accessibility, interpretability, usefulness, and believability. In order to be accessible to the user, the data must be *available* (exists in some form that can be accessed); to be useful, the data must be *relevant* (fits requirements for making the decision) and *timely*; and to be believable, the user may consider, among other factors, that the data be *complete, consistent, credible*, and *accurate*. Timeliness, in turn, can be characterized by *currency* (when the data item was stored in the database) and *volatility* (how long the item remains valid).

These multi-dimensional concepts and hierarchy of data quality dimensions provide a conceptual framework for understanding the characteristics that define data quality. In this paper, we focus on interpretability and believability, as we consider accessibility to be primarily a function of the information system and usefulness to be primarily a function of an interaction between the data and the application domain. The idea of data tagging is illustrated more concretely below.

Table 1
Company information

Company name	CEO name	Earnings estimate
IBM	Akers	7
DELL	Dell	3

Table 2
Company information with quality indicators

Company name	CEO name	Earnings estimate
IBM	Akers	7 ⟨source: Barron's, reporting-date: 10-05-92, data-entry-operator: Joe⟩
DELL	Dell	3 ⟨source: WSJ, reporting-date: 10-06-92, data-entry-operator: Mary⟩

1.2. Data quality: an attribute-based example

Suppose an analyst maintains a database on technology companies. The schema used to support this effort may contain attributes such as company name, CEO name, and earnings estimate (Table 1). Data may be collected over a period of time and come from a variety of sources.

As part of determining the believability of the data (assuming high interpretability), the analyst may want to know when the data was generated, where it came from, how it was originally obtained, and by what means it was recorded into the database. From Table 1, the analyst would have no means of obtaining this information. We illustrate in Table 2 an approach in which the data is tagged with quality indicators which may help the analyst determine the believability of the data.

As shown in Table 2, "7, ⟨source: Barron's, reporting-date: 10-05-92, data-entry-operator: Joe⟩" in Column 3 indicates that "*7 was the Earnings Estimate of IBM*" was reported in *Barron's* on *October 5, 1992* and was entered by *Joe*. An experienced analyst would know that Barron's is a *credible* source; that October 5, 1992 is *timely* (for example); and that Joe is experienced, therefore the data is likely to be *accurate*. As a result, he may conclude that the earnings estimate is *believable*. This example both illustrates the need for, and provides an example approach for, incorporating quality indicators into the database through data tagging.

1.3. Research focus and paper organization

The goal of the attribute-based approach is to facilitate the collection, storage, retrieval, and processing of data that has quality indicators. Central to the approach is the notion that a data attribute value may have a set of quality indicators associated with it. In some applications it may be necessary to know the quality of the quality indicators themselves. Thus, the model is constructed so that a quality indicator may, in turn, have another set of associated quality indicators. As such, an attribute may have an arbitrary number of underlying levels of quality indicators. This constitutes a tree structure, as shown in Figure 2.

Conventional spreadsheet programs and database systems are not appropriate for handling data which is structured in this manner. In particular, they lack needed quality integrity constraints necessary for ensuring that quality indicators are always tagged along with the data (and deleted when the data is deleted) and the algebraic operators necessary for attribute-based query processing. In order to associate an attribute with its immediate quality indicators, a mechanism must be developed to facilitate the linkage between the two, as well as between a quality indicator and the set of quality indicators associated with it.

This paper is organized as follows. Section 2 presents the research background. Section 3 presents the data quality requirements analysis methodology. In section 4, we present the attribute-based data model. Discussion and future directions are made in Section 5.

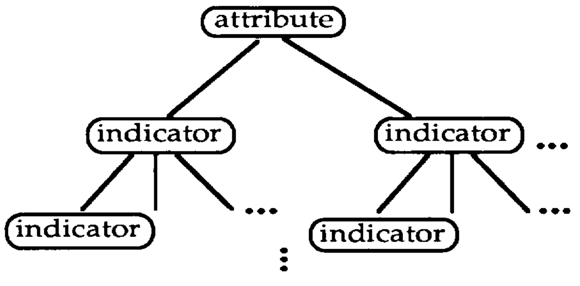


Fig. 2. An attribute with quality indicators.

2. Research background

In this section we discuss our rationale for tagging data at the cell level, summarize the literature related to data tagging, and present the terminology used in this paper.

2.1. Rationale for cell-level tagging

Any characteristics of data at the relation level should be applicable to all instances of the relation. It is, however, not reasonable to assume that all instances (i.e., tuples) of a relation have the same quality. Therefore, tagging quality indicators at the relation level is not sufficient to handle quality heterogeneity at the instance level.

By the same token, any characteristics of data tagged at the tuple level should be applicable to all attribute values in the tuple. However, each attribute value in a tuple may be collected from different sources, through different collection methods, and updated at different points in time. Therefore, tagging data at the tuple level is also insufficient. Since the attribute value of a cell is the basic unit of manipulation, it is necessary to tag quality information at the cell level.

We now examine the literature related to data tagging.

2.2. Work related to data tagging

A mechanism for tagging data has been proposed by Codd. It includes NOTE, TAG, and DENOTE operations to tag and un-tag the name of a relation to each tuple. The purpose of these operators is to permit both the schema information and the database extension to be manipulated in a uniform way [5]. It does not, however, allow for the tagging of other data (such as source) at either the tuple or cell level.

Although self-describing data files and metadata management have been proposed at the schema level [19,20,21], no specific solution has been offered to manipulate such quality information at the tuple and cell levels.

A rule-based representation language based on a relational schema has been proposed to store data semantics at the instance level [27].

These rules are used to derive meta-attribute values based on values of other attributes in the tuple. However, these rules are specified at the tuple level as opposed to the cell level, and thus cell-level operations are not inherent in the model.

A polygen model (poly = multiple, gen = source) [30] has been proposed to tag multiple data sources at the cell level in a heterogeneous database environment where it is important to know not only the originating data source but also the intermediate data sources which contribute to final query results. The research, however, was tailored to the "where from" perspective and did not provide mechanisms to deal with more general quality indicators.

In [26], annotations are used to support the temporal dimension of data in an object-oriented environment. However, data quality is a multi-dimensional concept. Therefore, a more general treatment is necessary to address the data quality issue. More importantly, no algebra or calculus-based language is provided to support the manipulation of annotations associated with the data.

The examination of the above research efforts suggests that in order to support the functionality of our attribute-based model, an extension of existing data models is required.

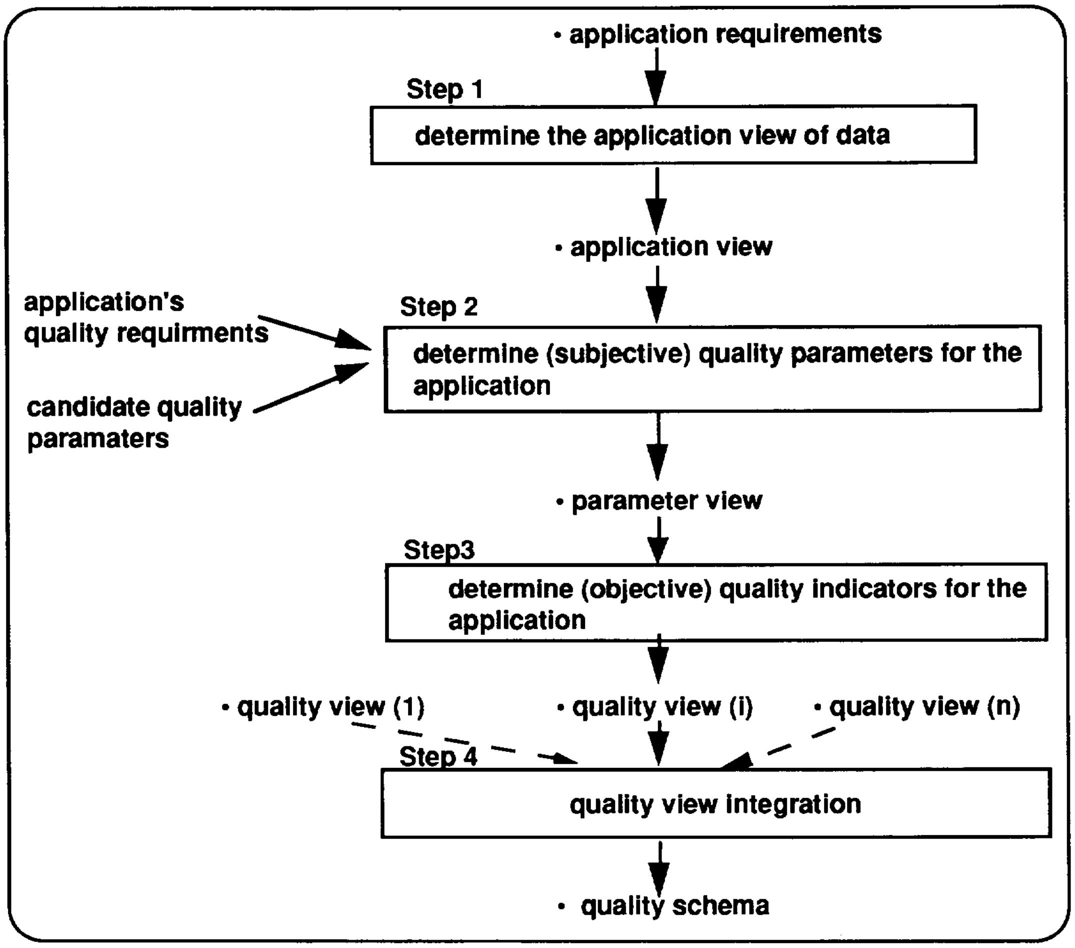

• application requirements
Step 1
determine the application view of data
• application view
Step 2
application's quality requirments
candidate quality paramaters
determine (subjective) quality parameters for the application
• parameter view
Step3
determine (objective) quality indicators for the application
• quality view (1)
• quality view (i)
• quality view (n)
Step 4
quality view integration
• quality schema

Fig. 3. The process of data quality requirements analysis.

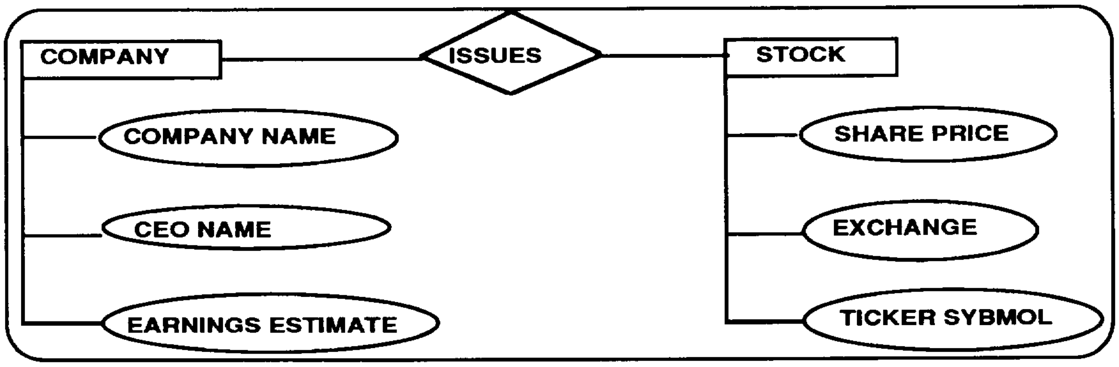


Fig. 4. Application view (output from Step 1).

2.3. Terminology

To facilitate further discussion, we introduce the following terms:

- An *application attribute* refers to an attribute associated with an *entity or a relationship* in an entity-relationship (ER) diagram. This would include the data traditionally associated with an application such as part number and supplier.
- A *quality parameter* is a qualitative or subjective dimension of data quality that a user of data defines when evaluating data quality. For example, *believability* and *timeliness* are such dimensions.
- As introduced in Section 1, *quality indicators* provide objective information about the characteristics of data and its manufacturing process [1]. *Data source, creation time*, and *collection method* are examples of such objective measures.
- A *quality parameter value* is the value determined (directly or indirectly) by the user of data for a particular quality parameter. This value is based on the values of underlying quality indicators. Functions can be defined by users to map quality indicators to quality parameters. For example, the quality parameter *credibility* may be defined as *high* or *low* depending on the quality indicator *source of the data*.
- A *quality indicator value* is a measured characteristic of the stored data. For example, the data quality indicator *source* may have a quality indicator value *The Wall Street Journal*.

We have discussed the rationale for cell-level tagging, summarized work related to data tagging, and introduced the terminology used in this paper. In the next section, we present a methodology for the specification of data quality parameters and indicators. The objective of the methodology is to allow users to think through their data quality requirements, and to determine which quality indicators would be appropriate for the given application.

3. Data quality requirements analysis

In general, different users may have different data quality requirements, and different types of data may have different quality characteristics. The reader is referred to the appendix for a more thorough treatment of these issues.

Data quality requirements analysis is an effort similar in spirit to traditional data requirements analysis [3,23,28], but focusing on quality aspects of the data. Based on this similarity, parallels can be drawn between traditional data requirements analysis and data quality requirements analysis.

[1] We consider an indicator objective if it is generated using a well defined and widely accepted measure.

Figure 3 depicts the steps involved in performing the proposed data quality requirements analysis.

The input, output and objective of each step are described in the following subsections.

3.1. Step 1: Establishing the applications view

Step 1 is the whole of the traditional data modeling process and will not be elaborated upon in this paper. A comprehensive treatment of the subject has been presented elsewhere [3,23,28].

For illustrative purposes, suppose that we are interested in designing a portfolio management system which contains companies that issue stocks. A company has a company name, a CEO, and an earnings estimate, while a stock has a share price, a stock exchange (NYSE, AMS, or OTC), and a ticker symbol. An ER diagram that documents the *application view* for our running example is shown in Figure 4.

3.2. Step 2: Determine (subjective) quality parameters

The goal in this step is to elicit quality parameters from the user given an application view. These parameters need to be gathered from the user in a systematic way as data quality is a multi-dimensional concept, and may be operationalized for tagging purposes in different ways. Figure 5 illustrates the addition of the two high level parameters, *interpretability* and *believability*, to the application view. Each quality parameter identified is shown inside a "cloud" in the diagram.

Interpretability can be defined through quality indicators such as *data units* (e.g., in dollars) and *scale* (e.g., in millions). *Believability* can be defined in terms of lower-level quality parameters such as *timeliness*, (data source) *credibility*, and *accuracy*. *Timeliness*, in turn, can be defined through *currency* and *volatility*. The quality parameters identified in this step are added to the application view. The resulting view is referred to as the *parameter view*. We focus here on the stock entity shown in Figure 6.

3.3. Step 3: Determine (objective) quality indicators

The goal in Step 3 is to operationalize the primarily subjective quality parameters identified in Step 2 into objective quality indicators. Each quality indicator is depicted as a tag (using a dotted-rectangle) and is attached to the corresponding quality parameter (from Step 2), creating the *quality view*. The portion of the quality view for the stock entity in the running example is shown in Figure 7.

Corresponding to the quality parameter *interpretable* are the more objective quality indicators (monetary) *units* in which share price is measured (e.g., \$ vs. ¥), and *status* which says whether the

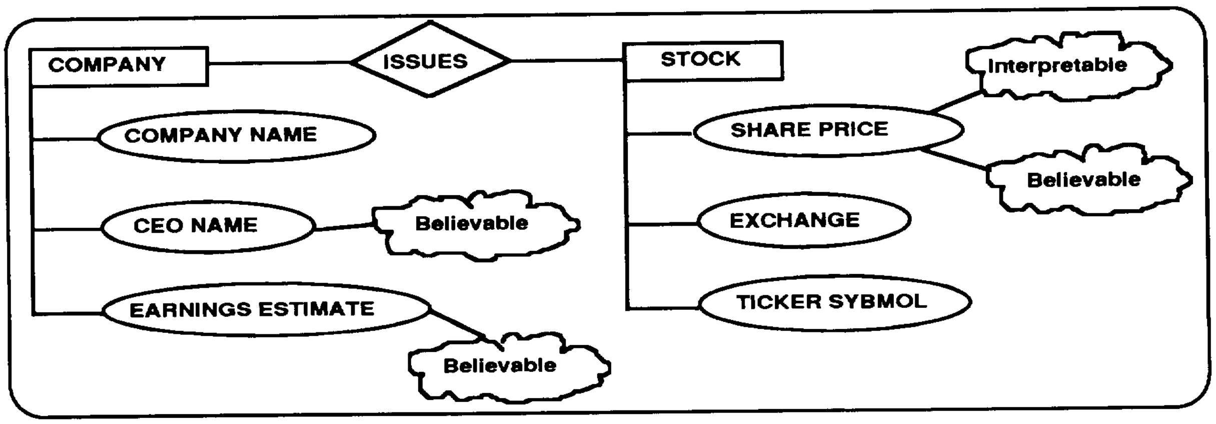


Fig. 5. Interpretability and believability added to the application view.

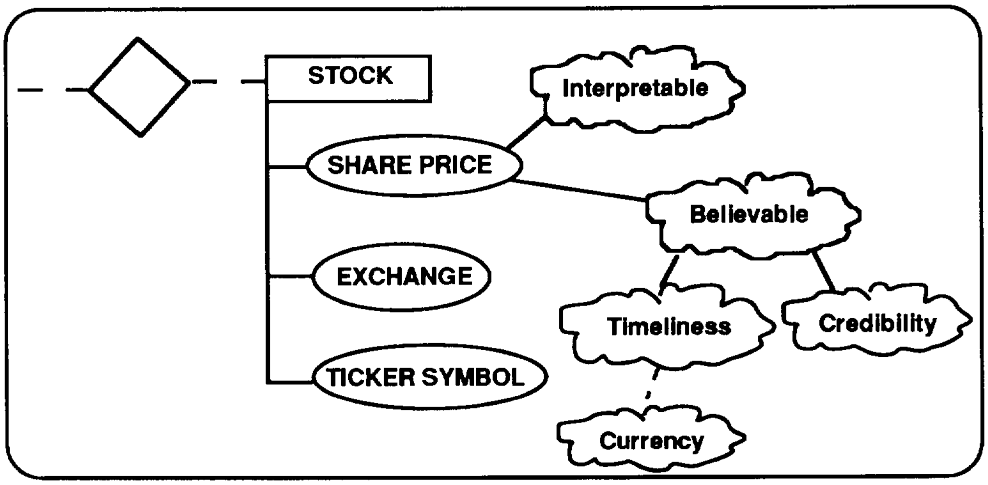


Fig. 6. Parameter view for the stock entity (partial output from Step 2).

share price is the latest closing price or latest nominal price. Similarly, the *believability* of the share price is indicated by the quality indicators (data) *source* and *reporting date*.

If it is important to have quality indicators for a quality indicator, then Steps 2-3 are repeated, making this an iterative process. For example, the quality of the attribute Earnings Estimate may depend not only on the first level source (the name of the journal) but also on the second level source (the name of the financial analyst who provided the Earnings Estimate figure to the journal and the Reporting date). This scenario is depicted below in Figure 8.

All quality views are integrated in Step 4 to generate the quality schema, as discussed in the following subsection.

3.4. Step 4: Creating the quality schema

When the design is large and more than one set of application requirements is involved, multi-

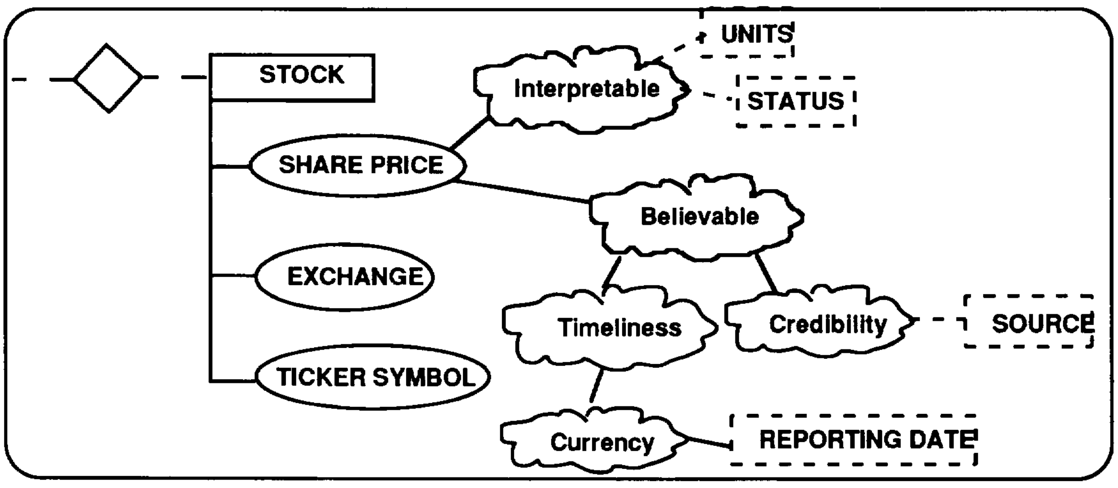


Fig. 7. The portion of the quality view for the stock entity (output from Step 3).

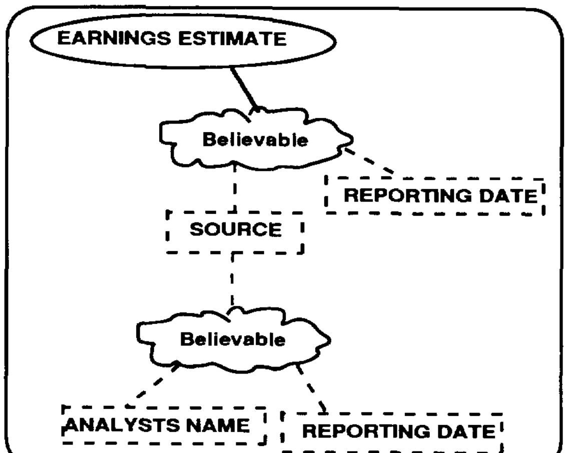


Fig. 8. Quality indicators of quality indicators.

ple quality views may result. To eliminate redundancy and inconsistency, these quality views must be consolidated into a single global view, in a process similar to schema integration [3], so that a variety of data quality requirements can be met. The resulting single global view is called the *quality schema*.

This involves the integration of quality indicators. In simpler cases, a union of these indicators may suffice. In more complicated cases, it may be necessary to examine the relationships among the indicators in order to decide what indicators to include in the quality schema. For example, it is likely that one quality view may have *age* as an indicator, whereas another quality view may have *creation time* for the same quality parameter. In this case, *creation time* may be chosen for the quality schema because age can be computed given current time and creation time.

We have presented a step-by-step procedure to specify data quality requirements. We are now in a position to present the attribute-based data model for supporting the storage, retrieval, and processing of quality indicators as specified in the quality schema.

4. The attribute-based model of data quality

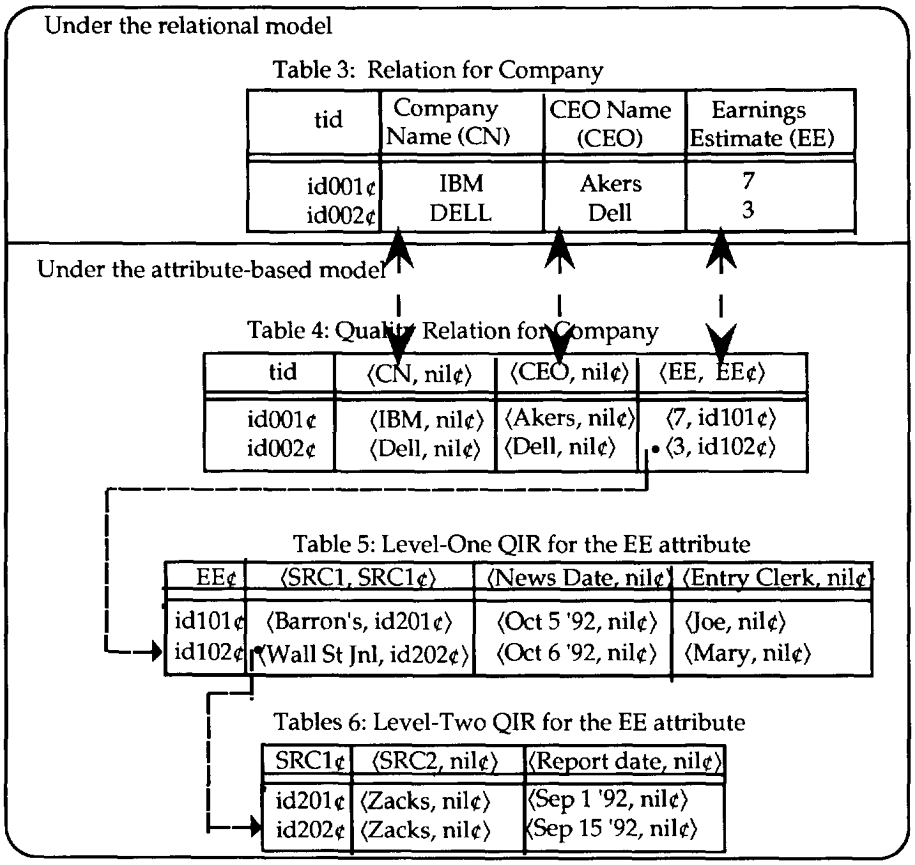
We choose to extend the relational model because the structure and semantics of the relational approach are widely understood. Following the relational model [6], the presentation of the attribute-based data model is divided into three parts: (a) data structure, (b) data integrity, and (c) data manipulation. We assume that the reader is familiar with the relational model [4,5,7,18].

4.1. Data structure

As shown in Figure 2 (Section 1), an attribute may have an arbitrary number of underlying levels of quality indicators. In order to associate an attribute with its immediate quality indicators, a mechanism must be developed to facilitate the linkage between the two, as well as between a quality indicator and the set of quality indicators associated with it. This mechanism is developed through the *quality key* concept. In extending the relational model, Codd made clear the need to uniquely identify tuples through a system-wide unique identifier, called the *tuple ID* [5,14]. This concept is used here to enable this linkage. Specifically, an attribute in a relation scheme is expanded into an ordered pair, called a *quality attribute*, consisting of the *attribute* and a *quality key*. The quality key is a reference to the underlying quality indicator(s).

For example, the attribute Earnings Estimate (EE) in Table 3 (Tables 3–6 are embedded in Figure 9) is expanded into ⟨EE, EE¢⟩ in Table 4 where EE¢ is the quality key for the attribute EE. This expanded scheme is referred to as a *quality scheme*. In Table 4, (⟨CN, nil¢⟩, ⟨CEO, nil¢⟩, ⟨EE, EE¢⟩) defines a quality scheme for the quality relation Company. The "nil¢" indicates that no quality indicators are associated with the attributes CN and CEO; whereas EE¢ indicates that EE has associated quality indicators.

Correspondingly, each cell in a relational tuple is expanded into an ordered pair, called a *quality cell*, consisting of an *attribute value* and a *quality key value*. This expanded tuple is referred to as a *quality tuple* and the resulting relation (Table 4) is referred to as a *quality relation*. Each quality key value in a quality cell refers to the set of quality indicator values immediately associated with the attribute value. This set of quality indicator values is grouped together to form a kind of quality



Under the relational model

Table 3: Relation for Company

tid	Company Name (CN)	CEO Name (CEO)	Earnings Estimate (EE)
id001¢	IBM	Akers	7
id002¢	DELL	Dell	3

Under the attribute-based model

Table 4: Quality Relation for Company

tid	⟨CN, nil¢⟩	⟨CEO, nil¢⟩	⟨EE, EE¢⟩
id001¢	⟨IBM, nil¢⟩	⟨Akers, nil¢⟩	⟨7, id101¢⟩
id002¢	⟨Dell, nil¢⟩	⟨Dell, nil¢⟩	⟨3, id102¢⟩

Table 5: Level-One QIR for the EE attribute

EE¢	⟨SRC1, SRC1¢⟩	⟨News Date, nil¢⟩	⟨Entry Clerk, nil¢⟩
id101¢	⟨Barron's, id201¢⟩	⟨Oct 5 '92, nil¢⟩	⟨Joe, nil¢⟩
id102¢	⟨Wall St Jnl, id202¢⟩	⟨Oct 6 '92, nil¢⟩	⟨Mary, nil¢⟩

Tables 6: Level-Two QIR for the EE attribute

SRC1¢	⟨SRC2, nil¢⟩	⟨Report date, nil¢⟩
id201¢	⟨Zacks, nil¢⟩	⟨Sep 1 '92, nil¢⟩
id202¢	⟨Zacks, nil¢⟩	⟨Sep 15 '92, nil¢⟩

Fig. 9. The quality scheme set for company.

tuple called a *quality indicator tuple*. A quality relation composed of a set of these time-varying quality indicator tuples is called a *quality indicator relation* (QIR). The quality scheme that defines the quality indicator relation is referred to as the *quality indicator scheme*.

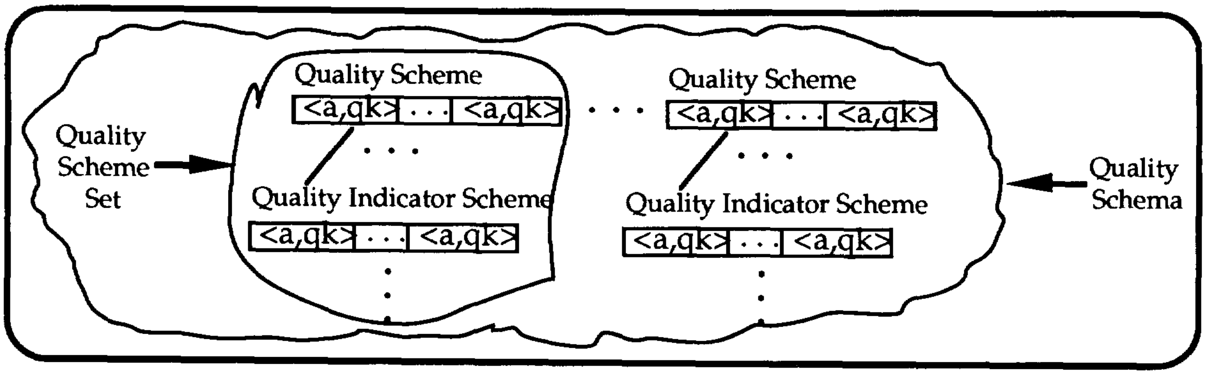


Fig. 10. Quality schemes, quality indicator schemes, quality scheme sets, and the quality schema.

The quality key thus serves as a foreign key, relating an attribute (or quality indicator) value to its associated quality indicator tuple. For example, Table 5 is a quality indicator relation for the attribute Earnings Estimate and Table 6 is a quality indicator relation for the attribute SRC1 (source of data) in Table 5. The quality cell ⟨Wall St Jnl, id202¢⟩ in Table 5 contains a quality key value, id202¢, which is a tuple id (primary key) in Table 6.

Let qr_l be a quality relation and a an attribute in qr_l. If a has associated quality indicators, then its quality key must be non-null (i.e., not "nil¢"). Let qr_2 be the quality indicator relation containing a quality indicator tuple for a, then all the attributes of qr_2 are called level-one quality indicators for a. Each attribute in qr_2, in turn, can have a quality indicator relation associated with it. In general, an attribute can have n-levels of quality indicator relations associated with it, $n \geqslant 0$. For example, Tables 5–6 are referred to respectively as level-one and level-two quality indicator relations for the attribute Earnings Estimate.

We define a *quality scheme set* as the collection of a quality scheme and all the quality indicator schemes that are associated with it. In Figure 9, Tables 3–6 collectively define the quality scheme set for Company. We *define a quality* database as a database that stores not only data but also quality indicators. A *quality schema* is defined as a set of quality scheme sets that describes the structure of a quality database. Figure 10 illustrates the relationship among quality schemes, quality indicator schemes, quality scheme sets, and the quality schema.

We now present a mathematical definition of the quality relation. Following the constructs developed in the relational model, we define a domain as a set of values of similar type. Let **ID** be the domain for a system-wide unique identifier (in Table 4, id101¢ ∈ ID). Let **D** be a domain for an attribute (in Table 4, 7 ∈ EE where EE is a domain for earnings estimate). Let **DID** be defined on the Cartesian product D X ID (in Table 4, ⟨7, *id*101¢⟩ ∈ *DID*).

Let *id* be a quality key value associated with an attribute value d where $d \in D$ and $id \in ID$. A *quality relation* of degree m is defined on the $m+1$ domains ($m > 0$; in Table 4, $m = 3$) if it is a subset of the Cartesian product:

$$\mathrm{ID} \times \mathrm{DID}_1 \times \mathrm{DID}_2 \times \ldots \times \mathrm{DID}_m.$$

Let qt be a quality tuple, which is an element in a quality relation. Then a quality relation qr is designated as:

$$qr = \{qt \mid qt = \langle id,\ did_1,\ did_2, \ldots, did_m \rangle \quad \text{where } id \in ID,\ did_j \in DIDj, j = 1, \ldots, m\}$$

The integrity constraints for the attribute-based model are presented next.

4.2. Data integrity

A fundamental property of the attribute-based model is that an attribute value and its corresponding quality (including all descendant) indicator values are treated as an atomic unit. By atomic unit we mean that when an attribute value is created, deleted, retrieved, or modified, its corresponding quality indicators may also need to be created, deleted, retrieved, or modified correspondingly. In other words, an attribute value and its quality indicator values behave atomically. We refer to this property as the atomicity property hereafter. This property is enforced by a set of quality referential integrity rules defined below.

Insertion: Insertion of a tuple in a quality relation must ensure that for each non-null quality key present in the tuple (as specified in the quality schema definition), the corresponding quality indicator tuple must be inserted into the child quality indicator relation. For each non-null quality key in the inserted quality indicator tuple, a corresponding quality indicator tuple must be inserted at the next level. This process must be continued recursively until no more insertions are required.

Deletion: Deletion of a tuple in a quality relation must ensure that for each non-null quality key present in the tuple, corresponding quality information must be deleted from the table corresponding to the quality key. This process must

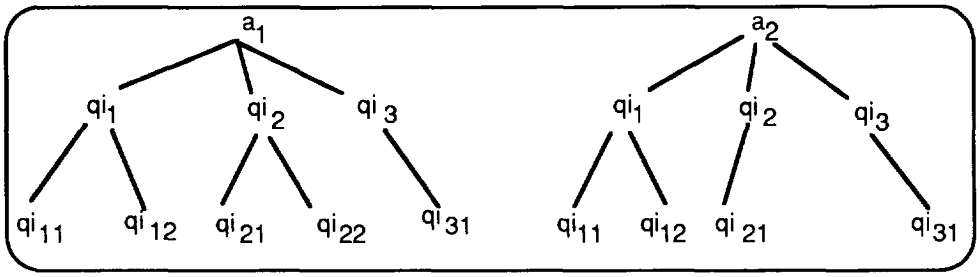


Fig. 11. QI-compatibility example.

be continued recursively until a tuple is encountered with all null quality keys.

Modification: If an attribute value is modified in a quality relation, then the descendant quality indicator values of that attribute must be modified.

We now introduce a quality indicator algebra for the attribute-based model.

4.3. Data manipulation

In order to present the algebra formally, we first define two key concepts that are fundamental to the quality indicator algebra: *QI-compatibility* and *QIV-Equal.*

4.3.1. QI-compatibility and QIV-equal

Let a_1 and a_2 be two application attributes. Let $\mathrm{QI}(a_i)$ denote the set of quality indicators associated with a_i. Let S be a set of quality indicators. If $S \subset \mathrm{QI}(a_1)$ and $S \subset \mathrm{QI}(a_2)$, then a_1 and a_2 are defined to be *QI-Compatible* with respect to S. We assume that the numeric subscripts (e.g., qi_{11}) map the quality indicators to unique positions (and semantics) in the quality indicator tree. For example, if S = $\{qi_1, qi_2, qi_{21}\}$, then the attributes a_1 and a_2 shown in Figure 11 are QI-Compatible with respect to S. Whereas if $S = \{qi_1, qi_{22}\}$, then the attributes a_1 and a_2 shown in Figure 11 are *not* QI-Compatible with respect to S.

Let a_1 and a_2 be QI-Compatible with respect to S. Let w_1 and w_2 be values of a_1 and a_2 respectively. Let $qi(w_1)$ be the value of quality indicator qfor the attribute value w_1 where $qi \in S$ ($qi_2(w_1) = v_2$ in Figure 12). Define w_1 and w_2 to be *QIV-Equal* with respect to S provided that $\forall qi \in S$ $qi(w_1) = qi(w_2)$, denoted as $w_1 =^S w_2$. In Figure 12, for example, w_1 and w_2 are QIV-Equal with respect to $S = \{qi_1, qi_{21}\}$, but *not* QIV-Equal with respect to $S = \{qi_1, qi_{31}\}$ because $qi_{31}(w_1) = v_{31}$ whereas $qi_{31}(w_2) = x_{31}$.

In practice, it is tedious to explicitly state all the quality indicators to be compared (i.e., to specify all the elements of S). To alleviate the situation, we introduce *i-level QI-compatibility* (*i-*

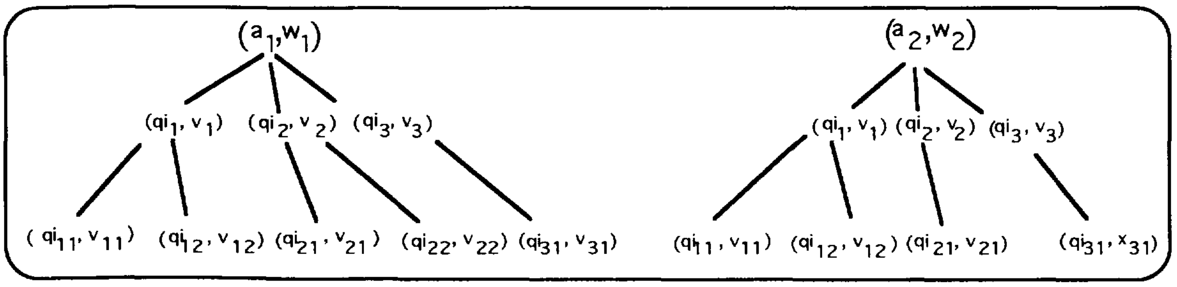


Fig. 12. QIV-equal example.

Table 7

<CN, nil¢>	<CEO, nil¢>	<EE, EE¢>
<IBM, nil¢>	<J Akers, nil¢>	<6.08, id0101¢>
<DEC, nil¢>	<K Olsen, nil¢>	<-0.32, id0102¢>
<TI, nil¢>	<J Junkins, nil¢>	<2.51, id0103¢>

Table 7.1

<EE¢, nil¢>	<SRC1, SRC1¢>	<Reporting_date, nil¢>
<id0101¢, nil¢>	<Nexis, id0201¢>	<10-07-92, nil¢>
<id0102¢, nil¢>	<Nexis, id0202¢>	<10-07-92, nil¢>
<id0103¢, nil¢>	<Lotus, id0203¢>	<10-07-92, nil¢>

Table 7.2

<SRC1¢, nil¢>	<SRC2, nil¢>	<Reporting_date, nil¢>
<id0201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>
<id0202¢, nil¢>	<First Boston, nil¢>	<1-07-92, nil¢>
<id0203¢, nil¢>	<First Boston, nil¢>	<1-07-92, nil¢>

Fig. 13. The quality relation large-and-medium.

level QIV-Equal) as a special case for QI-compatibility (QIV-equal) in which *all* the quality indicators up to a certain level of depth in a quality indicator tree are considered.

Let a_1 and a_2 be two application attributes. Let a_1 and a_2 be QI-Compatible with respect to S. Let w_1 and w_2 be values of a_1 and a_2 respectively, then w_1 and w_2 are defined to be *i-level QI-Compatible* if the following two conditions are satisfied: (1) a_1 and a_2 are QI-Compatible with respect to S, and (2) S consists of all quality indicators present within i levels of the quality indicator tree of a_1 (thus of a_2).

By the same token, i-level QIV-Equal between w_1 and w_2, denoted by $w_1 =^i w_2$, can be defined.

If "i" is the maximum level of depth in the

Table 8

<CN, nil¢>	<CEO, nil¢>	<EE, EE¢>
<Apple, nil¢>	<J Sculley, nil¢>	<5.69, id1101¢>
<DEC, nil¢>	<K Olsen, nil¢>	<-0.32, id1102¢>
<TI, nil¢>	<J Junkins, nil¢>	<2.51, id1103¢>

Table 8.1

<EE¢, nil>	<SRC1, SRC1¢>	<Reporting_date, nil¢>
<id1101¢, nil¢>	<Lotus, id1201¢>	<10-07-92, nil¢>
<id1102¢, nil¢>	<Nexis, id1202¢>	<10-07-92, nil¢>
<id1103¢, nil¢>	<Lotus, id1203¢>	<10-07-92, nil¢>

Table 8.2

<SRC1¢, nil¢>	<SRC2, nil¢>	<Reporting_date, nil¢>
<id1201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>
<id1202¢, nil¢>	<First Boston, nil¢>	<1-07-92, nil¢>
<id1203¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>

Fig. 14. The quality relation small-and-medium.

quality indicator tree, then a_1 and a_2 are defined to be *maximum-level QI-Compatible*. Similarly, *maximum-level QIV-Equal* between w_1 and w_2, denoted by $w_1 =^m w_2$, can also be defined.

To exemplify the algebraic operations in the quality indicator algebra, we introduce two quality relations having the same quality scheme set as shown in Figure 9. They are referred to as Large-and-Medium (Tables 7, 7.1, 7.2 in Figure 13) and Small-and-Medium (Tables 8, 8.1, and 8.2 in Figure 14).

These two quality relations will be used to illustrate various operations of the quality indicator algebra. In order to illustrate the relationship between the quality indicator algebraic operations and the high-level user query, the SELECT, FROM, WHERE structure of SQL is extended with an extra clause "with QUALITY." This extra clause enables a user to specify the quality requirements regarding an attributes referred to in a query.

If the clause "with QUALITY" is absent in a user query, then it means that the user has no explicit constraints on the quality of data that is being retrieved. In that case quality indicator values would not be compared in the retrieval process; however, the quality indicator values associated with the applications data would be retrieved as well.

In the extended SQL syntax, the dot notation is used to identify a quality indicator in the quality indicator tree. In Figure 9, for example, EE.SRC1.SRC2 identifies SRC2 which is a quality indicator for SRC1, which in turn is a quality indicator to EE.

The quality indicator algebra is presented in the following subsection.

4.3.2. Quality indicator algebra

Following the relational algebra [15], we define the five orthogonal quality relational algebraic operations, namely selection, projection, union, difference, and Cartesian product.

In the following operations, let *QR* and *QS* be two quality schemes and let *qr* and *qs* be two quality relations associated with *QR* and *QS* respectively. Let *a* and *b* be two attributes in both *QR* and *QS*. Let t_1 and t_2 be two quality tuples. Let S_a be a set of quality indicators specified by the user for the attribute *a*. (That is, S_a is constructed form the specifications given by the user in the "with QUALITY" clause.) Let the term $t_1.a = t_2.a$ denote that the values of the attribute *a* in the tuples t_1 and t_2 are identical. Let $t_1.a =^{Sa}$ t_2.a denote that the values of attribute *a* in the tuples t_1 and t_2 are QIV-equal with respect to S_a. Similarly, let $t_1.a =^i t_2.a$ and $t_1.a =^m t_2.a$ denote *i*-level QIV-equal and maximum-level QIV-equal respectively between the values of $t_1.a$ and $t_2.a$.

4.3.2.1. Selection. Selection is a unary operation which selects only a horizontal subset of a quality relation (and its corresponding quality indicator relations) based on the conditions specified in the Selection operation. There are two types of con-

Table 9

<CN, nil¢>	<CEO, nil¢>	<EE, EE¢>
<IBM, nil¢>	<J Akers, nil¢>	<6.08, id0101¢>

Table 9.1

<EE¢, nil¢>	<SRC1, SRC1¢>	<Reporting_date, nil¢>
<id0101¢, nil¢>	<Nexis, id0201¢>	<10-07-92, nil¢>

Table 9.2

<SRC1¢, nil¢>	<SRC2, nil¢>	<Reporting_date, nil¢>
<id0201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>

Fig. 15.

ditions in the Selection operation: regular conditions for an application attribute and quality conditions for the quality indicator relations corresponding to the application attribute. The selection, $\sigma_C^q(qr)$, is defined as follows:

$$\sigma_{\mathrm{C}}^{\mathrm{q}}(\mathrm{qr}) = \{\mathrm{t} \mid \forall \mathrm{t}_1 \in \mathrm{qr}, \forall \mathrm{a} \in \mathrm{QR}, ((\mathrm{t} \cdot \mathrm{a} = \mathrm{t}_1 \cdot \mathrm{a}) \wedge (\mathrm{t} \cdot \mathrm{a} =^{\mathrm{m}} \mathrm{t}_1.\mathrm{a})) \wedge \mathrm{C}(\mathrm{t}_1)\}$$

where $C(t_1) = e_1 \Phi e_2 \Phi \ldots \Phi e_n \Phi e_1^q \Phi e_2^q \Phi \ldots \Phi e_{\mathrm{p}}^q$; e_i is in one of the forms: ($t_1.a\ \theta$ constant) or ($t_1.a\ \theta\ t_1.b$); e_i^q is of the forms ($qi_k =$ constant) or $(t_1.a =^{Sa,b} t_1.b)$ or $(t_1.a =^{i} t_1.b)$ or $(t_1.a =^{m} t_1.b)$; $qi_k \in \mathrm{QI}(a)$; $\Phi \in \{\wedge, \vee, \neg\}$; $\theta \in \{= \leqq, \geq, \leq, \neq, <, >, =\}$; and $S_{a,b}$ is the set of quality indicators to be compared during the comparison of $t_1.a$ and $t_1.b$.

Example 1: Get all Large-and-Medium companies whose earnings estimate is over 2 and is supplied by Zacks Investment Research.

A corresponding extended SQL query is shown as follows:

```
SELECT          CN, CEO, EE
FROM            Large-and-Medium
WHERE           EE > 2
with QUALITY    EE.SRC1.SRC2 = "Zacks"
```

This SQL query can be accomplished through a Selection operation in the quality indicator algebra. The result is shown in Figure 15.

Note that in the conventional relational model, only Table 9 would be produced as a result of this SQL query. Whereas, in the quality indicator algebra, Tables 9.1, 9.2 are also produced. Table 9 shows that the earnings estimate for IBM is 6.08; and the quality indicator values in Tables 9.1 and 9.2 show that the data is retrieved from the Nexis database on October 7, 1992, which, in turn, is based on data reported by Zacks Investment Research on January 7, 1992. An experienced user could infer from these quality indicator values that the estimate is credible, given that Zacks is a reliable source of earnings estimates.

4.3.2.2. Projection. Projection is a unary operation which selects a vertical subset of a quality relation based on the set of attributes specified in the Projection operation. The result includes the projected quality relation and the corresponding quality indicator relations that are associated with the set of attributes specified in the Projection operation.

Let PJ be the attribute set specified, then the Projection, $\Pi_{\mathrm{PJ}}^{\mathrm{q}}$ (qr), is defined as follows:

$$\Pi_{\mathrm{PJ}}^{\mathrm{q}}(\mathrm{qr}) = \{\mathrm{t} \mid \forall \mathrm{t}_1 \in \mathrm{qr}, \forall \mathrm{a} \in \mathrm{PJ}, ((\mathrm{t.a} = \mathrm{t}_1 \cdot \mathrm{a}) \wedge (\mathrm{t.a} =^{\mathrm{m}} \mathrm{t}_1.\mathrm{a}))\}$$

<CN, nil¢>	<EE, EE¢>
<IBM, nil¢>	<6.08, id0101¢>
<DEC, nil¢>	<-0.32, id0102¢>
<TI, nil¢>	<2.51, id0103¢>

<EE¢, nil¢>	<SRC1, SRC1¢>	<Reporting_date, nil¢>
<id0101¢, nil¢>	<Nexis, id0201¢>	<10-07-92, nil¢>
<id0102¢, nil¢>	<Nexis, id0202¢>	<10-07-92, nil¢>
<id0103¢, nil¢>	<Lotus, id0203¢>	<10-07-92, nil¢>

<SRC1¢, nil¢>	<SRC2, nil¢>	<Reporting_date, nil¢>
<id0201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>
<id0202¢, nil¢>	<First Boston, nil¢>	<1-07-92, nil¢>
<id0203¢, nil¢>	<First Boston, nil¢>	<1-07-92, nil¢>

Fig. 16.

Example 2: Get company names and earnings estimates of all Large-and-Medium companies

A corresponding SQL query is shown as follows:

```
SELECT    CN, EE
FROM      Large-and-Medium
```

This SQL query can be accomplished through a Projection operation. The result is shown in Figure 16.

4.3.2.3. Union. In Union, the two operand quality relations must be QI-Compatible. The result includes (1) tuples from both qr and qs after elimination of duplicates, and (2) the corresponding quality indicator relations that are associated with the resulting tuples.

$$qr \cup^{q} qs = qr \cup \{t \mid \forall t_2 \in qs, \exists t_1 \in qr, \forall a \in QR,$$
$$((t.a = t_2.a) \wedge (t.a =^{m} t_2.a)$$
$$\wedge \neg((t_1.a = t_2.a) \wedge (t_1.a =^{Sa} t_2.a)))\}$$

In the above expression, "$\neg(t_1.a = t_2.a \wedge t_1.a =^{Sa} t_2.a)$" is meant to eliminate duplicates. Tuples t_1 and t_2 are considered duplicates provided that (1) there is a match between their corresponding attribute values (i.e., $t_1.a = t_2.a$) and (2) these values are QIV-equal with respect to the set of quality indicators (S_a) specified by the user (i.e., $t_1.a =^{Sa} t_2.a$).

Example 3-1: Get company names, CEO names, and earnings estimates of all Large-and-Medium and Small-and-Medium companies.

A corresponding extended SQL query is shown as follows:

```
SELECT         LM.CN, LM.CEO, LM.EE
FROM           Large-and-Medium LM
UNION
SELECT         SM.CN, SM.CEO, SM.EE
FROM           Small-and-Medium SM
with QUALITY   (LM.EE.SRC1.SRC2 = SM.
               EE.SRC1.SRC2)
```

This SQL query can be accomplished through a Union operation. The result is shown in Figure 17.

Note that there are two tuples corresponding to the company TI in the result because their quality indicator values are different with respect to SRC2.

Example 3-2: If the quality requirement were (LM.EE.SRC1 = SM.EE.SRC1) then these two

<CN, nil¢>	<CEO, nil¢>	<EE, EE¢>
<IBM, nil¢>	<J Akers, nil¢>	<6.08, id0101¢>
<DEC, nil¢>	<K Olsen, nil¢>	<-0.32, id0102¢>
<TI, nil¢>	<J Junkins, nil¢>	<2.51, id0103¢>
<Apple, nil¢>	<J Sculley, nil¢>	<5.69, id1101¢>
<TI, nil¢>	<J Junkins, nil¢>	<2.51, id1103¢>

<EE¢, nil¢>	<SRC1, SRC1¢>	<Reporting_date, nil¢>
<id0101¢, nil¢>	<Nexis, id0201¢>	<10-07-92, nil¢>
<id0102¢, nil¢>	<Nexis, id0202¢>	<10-07-92, nil¢>
<id0103¢, nil¢>	<Lotus, id0203¢>	<10-07-92, nil¢>
<id1101¢, nil¢>	<Lotus, id1201¢>	<10-07-92, nil¢>
<id1103¢, nil¢>	<Lotus, id1203¢>	<10-07-92, nil¢>

<SRC1¢, nil¢>	<SRC2, nil¢>	<Reporting_date, nil¢>
<id0201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>
<id0202¢, nil¢>	<First Boston, nil¢>	<1-07-92, nil¢>
<id0203¢, nil¢>	<First Boston, nil¢>	<1-07-92, nil¢>
<id1201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>
<id1203¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>

Fig. 17.

<CN, nil¢>	<CEO, nil¢>	<EE, EE¢>
<IBM, nil¢>	<J Akers, nil¢>	<6.08, id0101¢>
<DEC, nil¢>	<K Olsen, nil¢>	<-0.32, id0102¢>
<TI, nil¢>	<J Junkins, nil¢>	<2.51, id0103¢>
<Apple, nil¢>	<J Sculley, nil¢>	<5.69, id1101¢>

<EE¢, nil¢>	<SRC1, SRC1¢>	<Reporting_date, nil¢>
<id0101¢, nil¢>	<Nexis, id0201¢>	<10-07-92, nil¢>
<id0102¢, nil¢>	<Nexis, id0202¢>	<10-07-92, nil¢>
<id0103¢, nil¢>	<Lotus, id0203¢>	<10-07-92, nil¢>
<id1101¢, nil¢>	<Lotus, id1201¢>	<10-07-92, nil¢>

<SRC1¢, nil¢>	<SRC2, nil¢>	<Reporting_date, nil¢>
<id0201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>
<id0202¢, nil¢>	<First Boston, nil¢>	<1-07-92, nil¢>
<id0203¢, nil¢>	<First Boston, nil¢>	<1-07-92, nil¢>
<id1201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>

Fig. 18.

tuples would be considered duplicates and only one tuple for TI is retained in the result. The result of this query is shown in Figure 18.

Note also that unlike the relational union, the quality union operation is not commutative. This is illustrated in Example 3-3 below.

Example 3-3: Consider the following extended SQL query which switches the order of the union operation in Example 3-2:

```
SELECT      SM.CN, SM.CEO, SM.EE
FROM        Small-and-Medium SM
UNION
```

<CN, nil¢>	<CEO, nil¢>	<EE, EE¢>
<IBM, nil¢>	<J Akers, nil¢>	<6.08, id0101¢>
<DEC, nil¢>	<K Olsen, nil¢>	<-0.32, id0102¢>
<Apple, nil¢>	<J Sculley, nil¢>	<5.69, id1101¢>
<TI, nil¢>	<J Junkins, nil¢>	<2.51, id1103¢>

<EE¢, nil¢>	<SRC1, SRC1¢>	<Reporting_date, nil¢>
<id0101¢, nil¢>	<Nexis, id0201¢>	<10-07-92, nil¢>
<id0102¢, nil¢>	<Nexis, id0202¢>	<10-07-92, nil¢>
<id1101¢, nil¢>	<Lotus, id1201¢>	<10-07-92, nil¢>
<id1103¢, nil¢>	<Lotus, id1203¢>	<10-07-92, nil¢>

<SRC1¢, nil¢>	<SRC2, nil¢>	<Reporting_date, nil¢>
<id0201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>
<id0202¢, nil¢>	<First Boston, nil¢>	<1-07-92, nil¢>
<id1201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>
<id1203¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>

Fig. 19.

<CN, nil>	<CEO, nil¢>	<EE, EE>
<IBM, nil¢>	<J Akers, nil¢>	<6.08, id0101¢>
<TI, nil¢>	<J Junkins, nil¢>	<2.51, id0103¢>

<EE¢, nil>	<SRC1, SRC1¢>	<Reporting_date, nil¢>
<id0101¢, nil¢>	<Nexis, id0201¢>	<10-07-92, nil¢>
<id0103¢, nil¢>	<Lotus, id0203¢>	<10-07-92, nil¢>

<SRC1¢, nil>	<SRC2, nil¢>	<Reporting_date, nil¢>
<id0201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>
<id0203¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>

Fig. 20.

```
SELECT          LM.CN, LM.CEO, LM.EE
FROM            Large-and-Medium LM
with QUALITY  (LM.EE.SRC1 = SM.EE.SRC1)
```

The result is shown in Figure 19.

In the above result the tuple corresponding to TI is taken from Small-and-Medium companies. On the other hand, in Example 3-2 it is taken from the Large-and-Medium companies.

4.3.2.4. Difference. In Difference, the two operand quality relations must be QI-Compatible. The result of this operation consists of all tuples from *qr* which are not equal to tuples in *qs*. During this equality test the quality of attributes specified by the user for each attribute value in the tuples t_1 and t_2 will also be taken into consideration.

$$qr -^{q} qs = \{t \mid \forall t_1 \in qr, \exists t_2 \in qs, \forall a \in QR,$$
$$((t.a = t_1.a) \wedge (t.a =^{m} t_1.a))$$
$$\wedge \neg((t_1.a = t_2.a) \wedge (t_1.a =^{Sa} t_2.a))\}$$

Example 4: Get all the companies which are

<CN, nil¢>	<CEO, nil¢>	<EE, EE¢>
<IBM, nil¢>	<J Akers, nil¢>	<6.08, id0101¢>

<EE¢, nil¢>	<SRC1, SRC1¢>	<Reporting_date, nil¢>
<id0101¢, nil¢>	<Nexis, id0201¢>	<10-07-92, nil¢>

<SRC1¢, nil¢>	<SRC2, nil¢>	<Reporting_date, nil¢>
<id0201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>

Fig. 21.

classified as only Large-and-Medium companies but not as Small-and-Medium companies.

A corresponding SQL query is shown as follows:

```
SELECT          LM.CN, LM.CEO, LM.EE
FROM            Large-and-Medium LM
DIFFERENCE
SELECT          SM.CN, SM.CEO, SM.EE
FROM            Small-and-Medium SM
with QUALITY    (LM.EE.SRC1.SRC2 = SM.
                EE.SRC1.SRC2)
```

This SQL query can be accomplished through a Difference operation. The result is shown in Figure 20.

Note here that according to the conventional relational algebra, the tuple corresponding to the company TI must not be included in the result. But in quality indicator algebra the tuple corresponding to the company TI from the relation Large-and-Medium is included in the result because the corresponding tuple in the relation Small-and-Medium has different quality indicators than those of the relation Large-and-Medium. In the following paragraph, an example is provided to demonstrate the change in the contents of results when quality requirements change.

If the constraint in the QUALITY part of the

<LM.CN, nil¢>	<LM.CEO, nil¢>	<LM.EE, EE¢>	<SM.CN, nil¢>	<SM.CEO, nil¢>	<SM.EE, EE¢>
<IBM, nil¢>	<J Akers, nil¢>	<6.08,id0101¢>	<Apple, nil¢>	<J Sculley, nil¢>	<5.69, id1101¢>
<IBM, nil¢>	<J Akers, nil¢>	<6.08,id0101¢>	<DEC, nil¢>	<K Olsen, nil¢>	<-0.32, id1102¢>
<IBM, nil¢>	<J Akers, nil¢>	<6.08,id0101¢>	<TI, nil¢>	<J Junkins, nil¢>	<2.51, id1103¢>
<DEC, nil¢>	<K Olsen, nil¢>	<-0.32,id0102¢>	<Apple, nil¢>	<J Sculley, nil¢>	<5.69, id1101¢>
<DEC, nil¢>	<K Olsen, nil¢>	<-0.32,id0102¢>	<DEC, nil¢>	<K Olsen, nil¢>	<-0.32, id1102¢>
<DEC, nil¢>	<K Olsen, nil¢>	<-0.32,id0102¢>	<TI, nil¢>	<J Junkins, nil¢>	<2.51, id1103¢>
<TI, nil¢>	<J Junkins, nil¢>	<2.51,id0103¢>	<Apple, nil¢>	<J Sculley, nil¢>	<5.69, id1101¢>
<TI, nil¢>	<J Junkins, nil¢>	<2.51,id0103¢>	<DEC, nil¢>	<K Olsen, nil¢>	<-0.32, id1102¢>
<TI, nil¢>	<J Junkins, nil¢>	<2.51,id0103¢>	<TI, nil¢>	<J Junkins, nil¢>	<2.51, id1103¢>

<LM.EE¢, nil¢>	<LM.SRC1, SRC1¢>	<LM.Reporting_date,nil¢>
<id0101¢, nil¢>	<Nexis, d0201¢>	<10-07-92,nil¢>
<id0102¢, nil¢>	<Lotus, id0202¢>	<10-07-92,nil¢>
<id0103¢, nil¢>	<Nexis, id0203¢>	<10-07-92,nil¢>

<LM.SRC1¢, nil¢>	<LM.SRC2, nil¢>	<LM.Reporting_date,nil¢>
<id0201¢, nil¢>	<Zacks,nil¢>	<1-07-92,nil¢>
<id0202¢, nil¢>	<First Boston,nil¢>	<1-07-92,nil¢>
<id0203¢, nil¢>	<First Boston,nil¢>	<1-07-92,nil¢>

<SM.EE¢, nil>	<SM.SRC1, SRC1¢>	<SM.Reporting_date, nil¢>
<id1101¢, nil¢>	<Lotus, id1201¢>	<10-07-92, nil¢>
<id1102¢, nil¢>	<Nexis, id1202¢>	<10-07-92, nil¢>
<id1103¢, nil¢>	<Lotus, id1203¢>	<10-07-92, nil¢>

<SM.SRC1¢, nil¢>	<SM.SRC2, nil¢>	<SM.Reporting_date, nil¢>
<id1201¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>
<id1202¢, nil¢>	<First Boston, nil¢>	<1-07-92, nil¢>
<id1203¢, nil¢>	<Zacks, nil¢>	<1-07-92, nil¢>

Fig. 22.

query were (LM.EE.SRC1 = SM.EE.SRC1) then the result is as shown in Figure 21.

4.3.2.5. Cartesian product. The Cartesian product is also a binary operation. Let QR be of degree r and QS be of degree s. Let $t_1 \in qr$ and $t_2 \in qs$. Let $t_1(i)$ denote the i^{th} attribute of the tuple t_1 and $t_2(i)$ denote the i^{th} attribute of the tuple t_2. The tuple t in the quality relation resulting from the Cartesian product of qr and qs will be of degree $r+s$. The Cartesian product of qr and qs, denoted as $qr\, X^q\, qs$, is defined as follows:

$$
\begin{aligned}
qrX^q qs = \{t \mid \forall t_1 \in qr, \forall t_2 \in qs,\\
&(t(1) = t_1(1)) \wedge (t(1) =^m t_1(1))\\
&\wedge (t(2) = t_1(2)) \wedge (t(2) =^m t_1(2))\\
&\vdots\\
&\wedge (t(r) = t_1(r)) \wedge (t(r) =^m t_1(r))\\
&\wedge (t(r+1) = t_2(1)) \wedge (t(r+1) =^m t_2(1))\\
&\wedge (t(r+2) = t_2(2)) \wedge (t(r+2) =^m t_2(2))\\
&\vdots\\
&\wedge (t(r+s) = t_2(s)) \wedge (t(r+s) =^m t_2(s))\}
\end{aligned}
$$

The result of the Cartesian product between Large-and-Medium and Small-and-Medium is shown in Figure 22.

The set of quality indicator tables associated with each attribute in the table resulting from the Cartesian product are retrieved as part of the result.

Other algebraic operators such as Intersection and Join can be derived from these five orthogonal operators, as in relational algebra.

We have presented the attribute-based model including a description of the model structure, a set of integrity constraints for the model, and a quality indicator algebra. In addition, each of the algebraic operations are exemplified in the context of the SQL query. The next section discusses some of the capabilities of this model and future research directions.

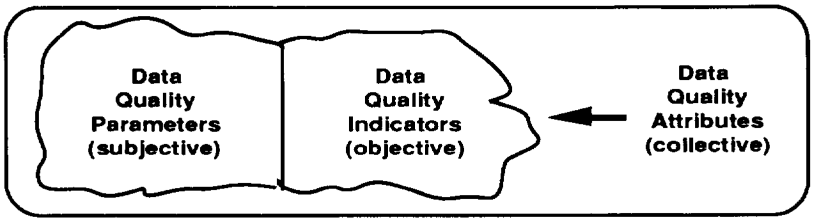
5. Discussion and future directions

The attribute-based model can be applied in different ways and some of them are listed below:

- The ability of the model to support quality indicators at multiple levels make it possible to retain the origin and intermediate data sources. The example in Figure 9 illustrates this.
- A user can filter the data retrieved from a database according to quality requirements. In Example 1, for instance, only the data furnished by Zacks Investment Research is retrieved as specified in the clause "with QUALITY EE.SRC1.SRC2 = "Zacks"."
- Data authenticity and believability can be improved by data inspection and certification. A quality indicator value could indicate who inspected or certified the data and when it was inspected. The reputation of the inspector will enhance the believability of the data.
- The quality indicators associated with data can help clarify data semantics, which can be used to resolve semantic incompatibility among data items received from different sources. This capability is very useful in an interoperable environment where data in different databases have different semantics.
- Quality indicators associated with an attribute may facilitate a better interpretation of null values. For example, if the value retrieved for the spouse field is empty in an employee record, it can be interpreted (i.e., tagged) in several ways, such as (1) the employee is unmarried, (2) the spouse name is unknown, or (3) this tuple is inserted into the employee table from the materialization of a view over a table which does not have spouse field.
- In a data quality control process, when errors are detected, the data administrator can identify the source of error by examining quality indicators such as data source or collection method.

In this paper, we have investigated how quality indicators may be specified, stored, retrieved, and processed. Specifically, we have (1) established a step-by-step procedure for data quality requirements analysis and specification, (2) presented a model for the structure, storage, and processing of quality relations and quality indicator relations, and (3) touched upon functionalities related to data quality administration and control.

We are actively pursuing research in the fol-


Data Quality Parameters (subjective)
Data Quality Indicators (objective)
Data Quality Attributes (collective)
Fig. 23. Relationship among quality attributes, quality parameters, and quality indicators.

lowing areas: (1) In order to determine the quality of derived data (e.g., combining accurate monthly data with less accurate weekly data), we are investigating mechanisms to determine the quality of derived data based on the quality indicator values of its components. (2) In order to use this model for existing databases, which do not have tagging capability, they must be extended with quality schemas instantiated with appropriate quality indicator values. We are exploring the possibility of making such a transformation cost-effective. (3) Though we have chosen the relational model to represent the quality schema, an object-oriented approach appears natural to model data and its quality indicators. Because many of the quality control mechanisms are procedure oriented and o-o models can handle procedures (i.e., methods), we are investigating the pros and cons of the object-oriented approach.

6. Acknowledgments

This work has been supported, in part, by MIT's International Financial Services Research Center (IFSRC) and by MIT's Total Data Quality Management (TDQM) research program. The authors wish to thank Stuart Madnick and the anonymous reviewers for their comments on earlier versions of this paper.

7. Appendix: Premises about data quality requirements analysis

Below we present premises related to data quality modeling and data quality requirements analysis. To facilitate further discussion, we define a *data quality attribute* as a collective term that refers to both quality parameters and quality indicators as shown in Figure 23 (This term is referred to as a *quality attribute* hereafter.)

7.1. Premises related to data quality modeling

Data quality modeling is an extension of traditional data modeling methodologies. As data modeling captures many of the structural and semantic issues underlying data, data quality modeling captures many of the structural and semantic issues underlying data quality. The following four premises relate to these data quality modeling issues.

⟨Premise 1.1⟩ (Relatedness between entity and quality attributes): In some cases a quality attribute can be considered either as an entity attribute (i.e., an application entity's attribute) or as a quality attribute. For example, the name of a teller who performs a transaction in a banking application may be an entity attribute if initial application requirements state that the teller's name be included; alternatively, it may be modeled as a quality attribute.

From a modeling perspective, whether an attribute should be modeled as an entity attribute or a quality attribute is a judgment call on the part of the design team, and may depend on the initial application requirements as well as eventual uses of the data, such as the inspection of the data for distribution to external users, or for integration with other data of different quality. The relevance of distribution and integration of the information is that often the users of a given system "know" the quality of the data they use. When the data is exported to their users, however, or combined with information of different quality, that quality may become unknown.

A guideline to this judgment is to ask what information the attribute provides. If the attribute provides application information such as a customer name and address, it may be considered an entity attribute. If, on the other hand, the information relates more to aspects of the data manufacturing process, such as when, where, and by whom the data was manufactured, then this may be a quality attribute.

In short, the objective of the data quality requirement analysis is not strictly to develop quality attributes, but also to ensure that important dimensions of data quality are not overlooked entirely in requirement analysis.

⟨Premise 1.2⟩ (Quality attribute non-orthogonality): Different quality attributes need not be orthogonal to one another. For example, the two quality parameters *credibility* and timeliness are related (i.e., not orthogonal), such as for real time data.

⟨Premise 1.3⟩ (Heterogeneity and hierarchy in the quality of supplied data): Quality of data may differ across databases, entities, attributes, and instances. Database example: information in a university database may be of higher quality than data in John Doe's personal database. Entity example: data about alumni (an entity) may be less reliable than data about students (an entity). Attribute example: in the student entity, grades may be more accurate than are addresses. Instance example: data about an international student may be less interpretable than that of a domestic student.

7.2. Premises related to data quality definitions and standards across users

Because human insight is needed for data quality modeling and different people may have different opinions regarding data quality, different quality definitions and standards may result. We call this phenomenon "data quality is in the eye of the beholder". The following two premises entail this phenomenon.

⟨Premise 2.1⟩ (Users define different quality attributes): Quality parameters and quality indicators may vary from one user to another. Quality parameter example: for a manager the quality parameter for a research report may be inexpensive, whereas for a financial trader, the research report may need to be credible and timely. Quality indicator example: the manager may measure inexpensiveness in terms of the quality indicator (monetary) cost, whereas the trader may measure inexpensiveness in terms of opportunity cost of her own time and thus the quality indicator may be retrieval time.

⟨Premise 2.2⟩ (Users have different quality standards): Acceptable levels of data quality may differ from one user to another. For example, an investor following the movement of a stock may consider a fifteen minute delay for share price to be sufficiently timely, whereas a trader who needs price quotes in real time may not consider fifteen minutes to be timely enough.

7.3. Premises related to a single user

A single user may have different quality attributes and quality standards for the different data used. This phenomenon is summarized in Premise 3 below.

⟨Premise 3⟩ (For a single user; non-uniform data quality attributes and standards): A user may have different quality attributes and quality standards across databases, entities, attributes, or instances. Across attributes example: A user may need higher quality information for the phone number than for the number of employees. Across instances example: A user may need high quality information for certain companies, but not for others due to the fact that some companies are of particular interest.

References

[1] D.P. Ballou and H.L. Pazer, Modelling Data and Process Quality in Multi-input, Multi-output Information Systems, *Management Science*, **31**(2), pp. 150–162 (1985).

[2] D.P. Ballou and H.L. Pazer, Cost/Quality Tradeoffs for Control Procedures in Information Systems, *International Journal of Management Science*, **15**(6), pp. 509–521 (1987).

[3] C. Batini, M. Lenzirini and S. Navathe, A comparative analysis of methodologies for database schema integration, *ACM Computing Survey*, **18**(4), pp. 323–364 (1986).

[4] E.F. Codd, A relational model of data for large shared data banks, *Communications of the ACM*, **13**(6), pp. 377–387 (1970).

[5] Codd, E.F. Extending the relational database model to capture more meaning, *ACM Transactions on Database Systems*, **4**(4), pp. 397–434 (1979).

[6] E.F. Codd, Relational database: A practical foundation for productivity, the 1981 ACM Turing Award Lecture, *Communications of the ACM*, **25**(2), pp. 109–117 (1982).

[7] C.J. Date, *An Introduction to Database Systems* (5th Ed.) Reading, MA: (Addison-Wesley, 1990).

[8] D.A. Garvin, Quality on the line, *Harvard Business Review*, pp. 65–75 (September-October, 1983).

[9] D.A. Garvin, Competing on the eight dimensions of quality, *Harvard Business Review*, pp. 101–109 (November-December, 1987).

[10] D.A. Garvin, *Managing Quality – The Strategic and Competitive Edge* (1 Ed.) New York: (The Free Press, 1988).

[11] Y.U. Huh et al. Data Quality, *Information and Software Technology*, **32**(8), pp. 559–565 (1990).

[12] J.R. Johnson and R.A. Leitch and J. Neter, Characteristics of Errors in Accounts Receivable and Inventory Audits, *Accounting Review*, **56**(April), pp. 270–293 (1981).

[13] J.M. Juran and F.M. Gryna, *Quality Planning and Analysis* (2nd Ed.) New York: (McGraw Hill, 1980).

[14] S.N. Khoshafian and G.P. Copeland, Object Identity, In S.B. Zdonik and D. Maier (Ed.), pp. 37–46. San Mateo, CA. (Morgan Kaufmann, 1990).

[15] A. Klug, Equivalence of relational algebra and relational calculus query languages having aggregate functions, *The Journal of ACM*, **29**, pp. 699–717 (1982).

[16] K.C. Laudon, Data Quality and Due Process in Large Interorganizational Record Systems, *Communications of the ACM*, **29**(1), pp. 4–11 (1986).

[17] G.E. Liepins and V.R. R Uppuluri, *Data Quality Control: Theory and Pragmatics*, New York (Marcel Dekker, Inc. 1990).

[18] D. Maier, *The Theory of Relational Databases* (1st Ed.) Rockville, MD: (Computer Science Press, 1983).

[19] J.L. McCarthy, *Metadata Management for Large Statistical Databases*, Mexico City, Mexico, pp. 234–243 (1982).

[20] J.L. McCarthy, *Scientific Information = Data + Metadata*, U.S. Naval Postgraduate School, Monterey, CA. (1984).

[21] J.L. McCarthy, *The Automated Data Thesaurus: A New Tool for Scientific Information*, Karlsruhe, Germany (1988).

[22] R.C. Morey, Estimating and Improving the Quality of Information in the MIS, *Communications of the ACM*, **25**(May), pp. 337–342 (1982).

[23] S. Navathe, C. Batini and S. Ceri, *The Entity Relationship Approach*, New york: (Wiley and Sons, 1992).

[24] E.T. O'Neill and D. Vizine-Goetz, Quality Control in Online Databases, In M.E. Williams (Ed.), pp. 125–156 (Elsevier Publishing Company, 1988).

[25] J.F. Rockart and J.E. Short, IT in the 1990s: Managing Organizational Interdependence, *Sloan Management Review, Sloan School of Management, MIT*, **30**(2), pp. 7–17 (1989).

[26] E. Sciore, Using Annotations to Support Multiple Kinds of Versioning in an Object-Oriented Database System, *ACM Transactions on Database Systems*, **16**, No. 3, pp. 417–438 (September 1991).

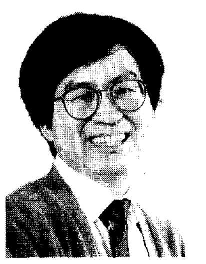
[27] M. Siegel and S.E. Madnick, *A metadata approach to resolving semantic conflicts*, Barcelona, Spain (1991).

[28] T.J. Teorey, *Database Modelling and Design: The Entity-Relationship Approach*, San Mateo, CA: (Morgan Kaufman Publisher, 1990).

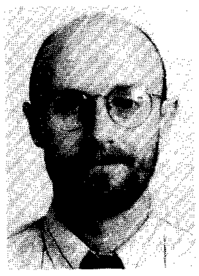
[29] R.Y. Wang and H.B. Kon, Towards Total Data Quality Management (TDQM), In R.Y. Wang (Ed.), (Chapter, pp. 179–197). Englewood Cliffs, NJ. (Prentice Hall, 1993).

[30] R.Y. Wang and S.E. Madnick, *A Polygen Model for Heterogeneous Database Systems: The Source Tagging Perspective*, Brisbane, Australia, pp. 519–538 (1990).

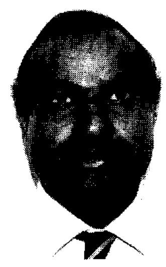
[31] R.Y. Wang, H.B. Kon and S.E. Madnick, *Data Quality Requirements Analysis and Modelling in Data Engineering*, Ninth International Conference on Data Engineering, Vienna, Austria, (1993).



Richard Y. Wang is Associate Professor of Information Technologies, MIT Sloan School of Management, where he received a Ph.D. degree with a concentration in Information Technologies. Dr. Wang has published extensively in the fields of data quality management, database management systems, and connectivity among information systems. He is also the editor of the book, Information Technologies: Trends and Perspectives (Prentice Hall, 1993). In addition, he teaches a number of IT-related courses at the graduate level, including one that provides a broad coverage of trends and perspectives in the computer industry. A principal investigator of several information technology related research projects, he has initiated a research program in Total Data Quality Management (TDQM). TDQM research investigates issues involved in data quality from both the technical and managerial perspectives. **Dr. Wang** is very active in professional services. He serves as a reviewer for many research journals, conferences and grant proposals. Most recently, he organized the annual Workshop on Information Technologies and Systems (WITS) which brings IT researchers and practitioners together to exchange ideas and results. Prior to joining MIT, he was on the faculty of the MIS Department of the University of Arizona, Tucson.



Henry B. Kon is a doctoral candidate in the Information Technologies program at the MIT Sloan School of Management. His experience includes core technology development in networking, database, and imaging technologies and he has application experience in the semiconductor, insurance, banking, transportation, and medical products industries. He has a B.S. in electrical engineering from Rutgers University, and an M.S. in computer science from New York University's Courant Institute of Mathematical Sciences. His research interests include data quality management and the integration of heterogeneous databases.



M. P. Reddy is a research associate in the Sloan School of Management at MIT. He holds a Master's degree in Physics and a Doctorate degree in Computer Science, from the University of Hyderabad, India. Dr. Reddy published several papers in the area of heterogeneous databases. His research interests include integration of heterogeneous databases, data quality management, and knowledge discovery in database systems.