Trends in Cleaning Relational Data: Consistency and Deduplication

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Contents

Abstract

Data quality is one of the most important problems in data management, since dirty data often leads to inaccurate data analytics results and wrong business decisions. Poor data across businesses and the government cost the U.S. economy \$3.1 trillion a year, according to a report by InsightSquared in 2012.

To detect data errors, data quality rules or integrity constraints (ICs) have been proposed as a declarative way to describe legal or correct data instances. Any subset of data that does not conform to the defined rules is considered erroneous, which is also referred to as a violation.

Various kinds of data repairing techniques with different objectives have been introduced, where algorithms are used to detect subsets of the data that violate the declared integrity constraints, and even to suggest updates to the database such that the new database instance conforms with these constraints. While some of these algorithms aim to minimally change the database, others involve human experts or knowledge bases to verify the repairs suggested by the automatic repeating algorithms.

In this paper, we discuss the main facets and directions in designing error detection and repairing techniques. We propose a taxonomy of current anomaly detection techniques, including error types, the automation of the detection process, and error propagation. We also propose a taxonomy of current data repairing techniques, including the repair target, the automation of the repair process, and the update model. We conclude by highlighting current trends in “big data” cleaning.

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Introduction

As businesses generate and consume data more than ever, enforcing and maintaining the quality of their data assets become critical tasks. One in three business leaders does not trust the information used to make decisions [36], since establishing trust in data becomes a challenge as the variety and the number of sources grow. For example, in health care domains, inaccurate or incorrect data may threaten patient safety [75].

Gartner predicted that more than 25% of critical data in the world's top companies is flawed [106]. Poor data across businesses and the government costs the U.S. economy $3.1 trillion a year, according to a report by InsightSquared [29]. With the increasing popularity of data science, it became evident that data curation, preparation, cleaning, and other "janitorial" data tasks, are key enablers in unleashing value of data, as indicated in a 2014 article in the New York Times[1].

Even when the data is ingested in JSON, XML, or text format, many of data quality assessment and cleaning activities happen after transforming the data into relational tables. There are many notions related to relational data quality: data consistency, data accuracy, data completeness, and data currency. Data consistency refers to the valid-

[1] http://nyti.ms/1t8IzfE

ity and integrity of data; data accuracy refers to how accurate the data values in a database with respect to the true values; data completeness indicates whether all the data needed to meet the information needs is available; and data currency, also known as, data timeliness, gives the degree to which the data is current with respect to the world or the process it models. There are various surveys and books on relational data quality. Rahm and Do [93] give a classification of different types of errors that can happen in an Extract-Transform-Load (ETL) process, and survey the tools available for cleaning data in an ETL process; some focus on the effect of incompleteness data on query answering [61], and the use of a Chase procedure for dealing with incomplete data [62]; Hellerstein [67] focuses on cleaning quantitative data, such as integers and floating points, using mainly statistical outlier detection techniques. Bertossi [8] provides complexity results for repairing inconsistent data, and performing consistent query answering on inconsistent data; Fan and Geerts [44] discuss the use of data quality rules in data consistency, data currency, and data completeness, how different aspects of data quality issues might interact; and Dasu and Johnson [33] summarize how techniques in exploratory data mining can be integrated with data quality management.

In this paper, we focus on the data consistency aspect of relational data quality. To ensure data consistency, data quality rules are often used. We use integrity constraints (ICs) to express data quality rules. Any part of the data that does not conform to a given set of ICs is considered erroneous, also known as a violation of ICs. Data deduplication can be seen as enforcing a key constraint defined on all the attributes of a relational schema, since two duplicate tuples can be seen as a violation of the key constraint. Data cleaning, in this context, is the exercise of detecting errors, and possibly modifying the database, such that the data conforms to a set of data quality rules expressed in a variety of languages. This paper covers techniques to detect data inconsistencies, as well as techniques to repair data inconsistencies.

The following example illustrates a real world tax record database that has various data quality problems due to the violations of different data quality rules, and the existence of duplicate records.

Example 1.1. Consider the US tax records in Table 1.1. Each record describes an individual's address and tax information with 15 attributes: first and last name (FN, LN), gender (GD), area code (AC), mobile phone number (PH), city (CT), state (ST), zip code (ZIP), marital status (MS), has children (CH), salary (SAL), tax rate (TR), tax exemption amount if single (STX), married (MTX), and having children (CTX).

The following constraints hold: (1) area code and phone identify a person; (2) two persons with the same zip code live in the same state; (3) a person who lives in Los Angeles lives in California; (4) if two persons live in the same state, the one with lower salary has a lower tax rate; (5) tax exemption is less than the salary.

A violation with respect to an IC is defined as the minimal subset of database cells, such that at least one of the cells has to be modified to satisfy the IC, where a cell is an attribute value of a tuple, *e.g.*, Cell t_1[FN] corresponds to Attribute FN of Tuple t_1 . For instance, the set of four cells $\{t_1[\text{ZIP}], t_8[\text{ZIP}], t_1[\text{ST}], t_8[\text{ST}]\}$ is a violation with respect to the second constraint. Furthermore, Record t_4 and t_9 refer to the same person, even though t_4[FN] and t_9[FN] are different, and t_9[AC] is empty. Given a relational database instance I of schema R and a set of integrity constraints Σ, we need to find another database instance I' with no violations with respect to Σ.

1.1 Notations

Let R denote a relational schema, and I be an instance of that schema. Attributes of R are denoted as $attr(R) = \{A_1, \ldots, A_m\}$. For each Attribute A in R, let $Dom(A)$ denote the domain of A. I consists of a set of tuples, each of which belongs to the domain $Dom(A_1) \times \ldots \times Dom(A_m)$. We assume that there is a unique tuple identifier associated with each tuple $t \in I$. Let $TIDs(I)$ denote the set of all tuple identifiers. We identify a cell of Attribute A of a tuple t in I by $I(t[A])$, simply referred to as $t[A]$ when the context is clear. Let $CIDs(I)$ denote the set of all cell identifiers in I.

TID	FN	LN	GD	AC	PH	CT	ST	ZIP	MS	CH	SAL	TR	STX	MTX	CTX
t_1	Mark	Ballin	M	304	232-7667	Anthony	WA	25813	S	Y	70000	3	2000	0	2000
t_2	Chunho	Black	M	206	154-4816	Seattle	WA	98103	M	N	60000	4.63	0	0	0
t_3	Annja	Rebizant	F	636	604-2692	Cyrene	MO	64739	M	N	40000	6	0	4200	0
t_4	Annie	Puerta	F	501	378-7304	West Crossett	AR	72045	M	N	85000	7.22	0	40	0
t_5	Anthony	Landram	M	319	150-3642	Gifford	IA	52404	S	Y	15000	2.48	40	0	40
t_6	Mark	Murro	M	970	190-3324	Denver	CO	80251	S	Y	60000	4.63	0	0	0
t_7	Ruby	Billinghurst	F	501	154-4816	Kremlin	AR	72045	M	Y	70000	7	0	35	1000
t_8	Marcelino	Nuth	F	304	540-4707	Kyle	WV	25813	M	N	10000	4	0	0	0
t_9	Ann	Puerta	F		378-7304	West Crossett	AR	72045	M	N	86000	7.22	0	40	0

Table 1.1: Tax data records.

1.2 Outline

The remainder of the paper is organized as follows. Section 2 discusses different ways to detect anomalies in the data, such as data duplication, integrity constraints languages, along with algorithms for their automatic discovery, and provenance-based error propagation, based on what, how, and where to detect. Section 3 introduces the taxonomy we adopt to classify data repairing techniques, based on what, how, and where to repair, and presents the details of multiple techniques in each dimension. Section 4 discusses the techniques proposed for dealing with big data cleaning. Section 5 concludes and summarizes future research directions.

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