Causality in Databases: The Diagnosis and Repair Connections

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Abstract

In this work we establish and investigate the connections between causality for query answers in databases, database repairs wrt. denial constraints, and consistency-based diagnosis. The first two are relatively new problems in databases, and the third one is an established subject in knowledge representation. We show how to obtain database repairs from causes and the other way around. The vast body of research on database repairs can be applied to the newer problem of determining actual causes for query answers. By formulating a causality problem as a diagnosis problem, we manage to characterize causes in terms of a system's diagnoses.

1 Introduction

When querying a database, a user may not always obtain the expected results, and the system could provide some explanations. They could be useful to further understand the data or check if the query is the intended one. Actually, the notion of explanation for a query result was introduced in (Meliou et al. 2010a), on the basis of the deeper concept of *actual causation*.

Intuitively, a tuple t is a *cause* for an answer $\bar{a}$ to a conjunctive query $\mathcal{Q}$ from a relational database instance D if there is a "contingent" set of tuples Γ, such that, after removing Γ from D, removing/inserting t from/into D causes $\bar{a}$ to switch from being an answer to being a non-answer. Actual causes and contingent tuples are restricted to be among a pre-specified set of *endogenous tuples*, which are admissible, possible candidates for causes, as opposed to *exogenous tuples*.

Some causes may be stronger than others. In order to capture this observation, (Meliou et al. 2010a) also introduces and investigates a quantitative metric, called *responsibility*, which reflects the relative degree of causality of a tuple for a query result. In applications involving large data sets, it is crucial to rank potential causes by their responsibility (Meliou et al. 2010b; Meliou et al. 2010a).

Actual causation, as used in (Meliou et al. 2010a), can be traced back to (Halpern, and Pearl 2001; Halpern, and Pearl 2005), which provides a model-based account of causation on the basis of the *counterfactual dependence*. Responsibility was also introduced in (Chockler, and Halpern 2004), to capture the *degree of causation*.

Apart from the explicit use of causality, research on explanations for query results has focused mainly, and rather implicitly, on provenance (Buneman, Khanna, and Tan 2001; Buneman, and Tan 2007; Cheney, Chiticariu, and Tan 2009; Cui, Widom, and Wiener 2000; Karvounarakis, Ives, and Tannen 2010; Karvounarakis, and Green 2012; Tannen 2013), and more recently, on provenance for non-answers (Chapman, and Jagadish 2009; Huang et al. 2008).[1] A close connection between causality and provenance has been established (Meliou et al. 2010a). However, causality is a more refined notion that identifies causes for query results on the basis of user-defined criteria, and ranks causes according to their responsibility (Meliou et al. 2010b). For a formalization of non-causality-based explanations for query answers in DL ontologies, see (Borgida, Calvanese, and Rodriguez-Muro 2008).

Consistency-based diagnosis (Reiter 1987), a form of model-based diagnosis (Struss 2008, sec. 10.3), is an area of knowledge representation. The main task here is, given the *specification* of a system in some logical formalism and a usually unexpected *observation* about the system, to obtain *explanations* for the observation, in the form of a diagnosis for the unintended behavior.

In a different direction, a database instance, D, that is expected to satisfy certain integrity constraints (ICs) may fail to do so. In this case, a *repair* of D is a database D' that does satisfy the ICs and *minimally departs* from D. Different forms of minimality can be applied and investigated. A *consistent answer* to a query from D and wrt. the ICs is a query answer that is obtained from all possible repairs, i.e. is invariant or certain under the class of repairs. These notions were introduced in (Arenas, Bertossi, and Chomicki 1999) (see (Bertossi 2011) for a recent survey). We should mention that, although not in the framework of database repairs, consistency-based diagnosis techniques have been applied to restoring consistency of a database wrt. a set of ICs (Gertz 1997)

These three forms of reasoning, namely inferring causality in databases, consistency-based diagnosis, and consistent

[1] That is, tracing back, sometimes through the interplay of database tuple annotations, the reasons for *not* obtaining a possibly expected answer to a query.

query answers (and repairs) are all *non-monotonic*. For example, a (most responsible) cause for a query result may not be such anymore after the database is updated. In this work we establish natural, precise, useful, and deeper connections between these three reasoning tasks.

We show that inferring and computing actual causes and responsibility in a database setting become, in different forms, consistency-based diagnosis reasoning problems and tasks. Informally, a causal explanation for a conjunctive query answer can be viewed as a diagnosis, where in essence the first-order logical reconstruction of the relational database provides the system description (Reiter 1982), and the observation is the query answer. Furthermore, we unveil a strong connection between computing causes and their responsibilities for conjunctive queries, on the one hand, and computing *repairs* in databases (Bertossi 2011) wrt. denial constraints, on the other hand. These computational problems can be reduced to each other.

More precisely, our results are as follows:

1. For a boolean conjunctive query and its associated denial constraint (which is violated iff the query is true), we establish a precise connection between actual causes for the query (being true) and the subset-repairs of the instance wrt. the constraint. Namely, we obtain causes from repairs.
2. In particular, we establish the connection between an actual cause's responsibility and cardinality repairs wrt. the associated constraint.
3. We characterize and obtain subset- and cardinality- repairs for a database under a denial constraint in terms of the causes for the associated query being true.
4. We consider *a set* of denials constraints and a database that may be inconsistent wrt. them. We obtain the database repairs by means of an algorithm that takes as input the actual causes for constraint violations and their contingency sets.
5. We establish a precise connection between consistency-based diagnosis for a boolean conjunctive query being unexpectedly true according to a system description, and causes for the query being true. In particular, we can compute actual causes, their contingency sets, and responsibilities from minimal diagnosis.
6. Being this a report on ongoing work, we discuss several extensions and open issues that are under investigation.

2 Preliminaries

We will consider relational database schemas of the form $\mathcal{S} = (U, \mathcal{P})$, where U is the possibly infinite database domain and $\mathcal{P}$ is a finite set of database predicates of fixed arities. A database instance D compatible with $\mathcal{S}$ can be seen as a finite set of ground atomic formulas (in databases aka. atoms or tuples), of the form $P(c_1, ..., c_n)$, where $P \in \mathcal{P}$ has arity n, and $c_1, \ldots, c_n \in U$. A conjunctive query is a formula $\mathcal{Q}(\bar{x})$ of the first-order (FO) logic language, $\mathcal{L}(\mathcal{S})$, associated to $\mathcal{S}$ of the form $\exists \bar{y}(P_1(\bar{t}_1) \wedge \cdots \wedge P_m(\bar{t}_m))$, where the $P_i(\bar{t}_i)$ are atomic formulas, i.e. $P_i \in \mathcal{P}$, and the $\bar{t}_i$ are sequences of terms, i.e. variables or constants of U. The $\bar{x}$ in $\mathcal{Q}(\bar{x})$ shows all the free variables in the formula, i.e. those not appearing in $\bar{y}$. The query is boolean, if $\bar{x}$ is empty, i.e. the query is a sentence, in which case, it is true or false in a database, denoted by $D \models \mathcal{Q}$ and $D \not\models \mathcal{Q}$, respectively. A sequence $\bar{c}$ of constants is an answer to an open query $\mathcal{Q}(\bar{x})$ if $D \models \mathcal{Q}[\bar{c}]$, i.e. the query becomes true in D when the variables are replaced by the corresponding constants in $\bar{c}$.

An integrity constraint is a sentence of language $\mathcal{L}(\mathcal{S})$, and then, may be true or false in an instance for schema $\mathcal{S}$. Given a set *IC* of ICs, a database instance D is *consistent* if $D \models IC$; otherwise it is said to be *inconsistent*. In this work we assume that sets of ICs are always finite and logically consistent. A particular class of integrity constraints (ICs) is formed by *denial constraints* (DCs), which are sentences κ of the from: $\forall \bar{x} \neg(A_1(\bar{x}_1) \wedge \cdots \wedge A_n(\bar{x}_n))$, where $\bar{x} = \bigcup \bar{x}_i$ and each $A_i(\bar{x}_i)$ is a database atom, i.e. predicate $A \in \mathcal{P}$. DCs will receive special attention in this work. They are common and natural in database applications since they disallow combinations of database atoms.

Causality and Responsibility. Assume that the database instance is split in two, i.e. $D = D^n \cup D^x$, where D^n and D^x denote the sets of *endogenous* and *exogenous* tuples, respectively. A tuple $t \in D^n$ is called a *counterfactual cause* for a boolean conjunctive $\mathcal{Q}$, if $D \models \mathcal{Q}$ and $D \smallsetminus \{t\} \not\models \mathcal{Q}$. A tuple $t \in D^n$ is an *actual cause* for $\mathcal{Q}$ if there exists $\Gamma \subseteq D^n$, called a *contingency set*, such that t is a counterfactual cause for $\mathcal{Q}$ in $D \smallsetminus \Gamma$ (Meliou et al. 2010a).

The *responsibility* of an actual cause t for $\mathcal{Q}$, denoted by $\rho(t)$, is the numerical value $\frac{1}{(|\Gamma|+1)}$, where $|\Gamma|$ is the size of the smallest contingency set for t. We can extend responsibility to all the other tuples in D^n by setting their value to 0. Those tuples are not actual causes for $\mathcal{Q}$.

In (Meliou et al. 2010a), causality for non-query answers is defined on basis of sets of *potentially missing tuples* that account for the missing answer. Computing actual causes and their responsibilities for non-answers becomes a rather simple variation of causes for answers. In this work we focus on causality for query answers.

Example 1. Consider a database D with relations R and S as below, and the query $\mathcal{Q} : \exists x \exists y(S(x) \wedge R(x, y) \wedge S(y))$. $D \models \mathcal{Q}$ and we want to find causes for $\mathcal{Q}$ being true in D under the assumption that all tuples are endogenous.

R	X	Y
	a_4	a_3
	a_2	a_1
	a_3	a_3

S	X
	a_4
	a_2
	a_3

Tuple $S(a_3)$ is a counterfactual cause for $\mathcal{Q}$. If $S(a_3)$ is removed from D, we reach a state where $\mathcal{Q}$ is no longer an answer. Therefore, the responsibility of $S(a_3)$ is 1. Besides, $R(a_4, a_3)$ is an actual cause for $\mathcal{Q}$ with contingency set $\{R(a_3, a_3)\}$. If $R(a_3, a_3)$ is removed from D, we reach a state where $\mathcal{Q}$ is still an answer, but further removing $R(a_4, a_3)$ makes $\mathcal{Q}$ a non-answer. The responsibility of $R(a_4, a_3)$ is $\frac{1}{2}$, because its smallest contingency sets have size 1. Likewise, $R(a_3, a_3)$ and $S(a_4)$ are actual causes for $\mathcal{Q}$ with responsibility $\frac{1}{2}$. $\square$

Now we can show that counterfactual causality for query answers is a non-monotonic notion.

Example 2. (ex. 1 cont.) Consider the same query $\mathcal{Q}$, but now the database instance $D = \{S(a_3), S(a_4), R(a_4, a_3)\}$, with the partition $D^n = \{S(a_4), S(a_3)\}$ and $D^x = \{R(a_4, a_3)\}$. Both $S(a_3)$ and $S(a_4)$ are counterfactual causes for $\mathcal{Q}$.

Now assume $R(a_3, a_3)$ is added to D as an exogenous tuple, i.e. $(D^x)' = \{R(a_4, a_3),\ R(a_3, a_3)\}$. Then, $S(a_4)$ is no longer a counterfactual cause for $\mathcal{Q}$ in $D' = D^n \cup (D^x)'$: If $S(a_4)$ is removed from the database, $\mathcal{Q}$ is still true in D'. Moreover, $S(a_4)$ not an actual cause anymore, because there is no contingency set that makes $S(a_4)$ a counterfactual cause.

Notice that, if $R(a_3, a_3)$ is instead inserted as an endogenous tuple, i.e. $(D^n)' = \{S(a_4), S(a_3), R(a_3, a_3)\}$, then, $S(a_4)$ is still an actual cause for $\mathcal{Q}$, with contingency set $\{R(a_3, a_3)\}$. $\square$

The following proposition shows that the notion of actual causation is non-monotone in general.

Notation: $\mathcal{CS}(D^n, D^x, \mathcal{Q})$ denotes the set of actual causes for BCQ $\mathcal{Q}$ (being true) from instance $D = D^n \cup D^x$. When $D^n = D$ and $D^x = \emptyset$, we sometimes simply write: $\mathcal{CS}(D, \mathcal{Q})$.

Proposition 1. Let $(D^n)', (D^x)'$ denote updates of instances D^n, D^x by insertion of tuple t, resp. It holds: (a) $\mathcal{CS}(D^n, D^x,\ \mathcal{Q}) \subseteq \mathcal{CS}((D^n)', D^x, \mathcal{Q})$. (b) $\mathcal{CS}(D^n, (D^x)', \mathcal{Q}) \subseteq \mathcal{CS}(D^n, D^x, \mathcal{Q})$. $\square$

Example 2 shows that the inclusion in (b) may be strict. It is easy to show that it can also be strict for (a). This result tells us that, for a fixed query, inserting an endogenous tuples may extend the set of actual cases, but it may shrink by inserting an endogenous tuple. It is also easy to verify that most responsible causes may not be such anymore after the insertion of endogenous tuples.

Database Repairs. Given a set *IC* of ICs, a *subset-repair* (simply, S-repair) of a possibly inconsistent instance D for schema $\mathcal{S}$ is an instance D' for $\mathcal{S}$ that satisfies *IC* and makes $\Delta(D, D') = (D \smallsetminus D') \cup (D' \smallsetminus D)$ minimal under set inclusion. $\mathit{Srep}(D, \mathit{IC})$ denotes the set of S-repairs of D wrt. *IC* (Arenas, Bertossi, and Chomicki 1999). $\bar{c}$ is a *consistent answer* to query $\mathcal{Q}(\bar{x})$ if $D' \models \mathcal{Q}[\bar{c}]$ for every $D' \in \mathit{Srep}$, denoted $D \models_S \mathcal{Q}[\bar{c}]$. S-repairs and consistent query answers for DCs were investigated in detail (Chomicki, and Marcinkowski 2005). (Cf. (Bertossi 2011) for more references.)

Similarly, D' is a *cardinality repair* (simply C-repair) of D if D' satisfies *IC* and minimizes $|\Delta(D, D')|$. $\mathit{Crep}(D, \mathit{IC})$ denotes the class of C-repairs of D wrt. *IC*. That $\bar{c}$ is a consistent answer to $\mathcal{Q}(\bar{x})$ wrt. C-repairs is denoted by $D \models_C \mathcal{Q}[\bar{c}]$. C-repairs were investigated in detail in (Lopatenko, and Bertossi 2007).

C-repairs are S-repairs of minimum cardinality, and, for DCs, they are obtained from the original instance by deleting a cardinality-minimum or a subset-minimal set of tuples, respectively. Obtaining repairs and consistent answers is a non-monotonic process. That is, after an update of D to $u(D)$, obtained by tuple insertions, a repair or a consistent answer for D may not be such for $u(D)$ (Bertossi 2011).

Consistency-Based Diagnosis. The starting point of this consistency-based approach to diagnosis is a diagnosis problem of the form $\mathcal{M} = (\mathit{SD}, \mathit{COMPS}, \mathit{OBS})$, where SD is the description in logic of the intended properties of a system under the *explicit* assumption that all its components, those in the set of constants *COMPS*, are normal (or working normally). OBS is a finite set of FO sentences (usually a conjunction of ground literals) that represents the observations.

Now, if the system does not behave as expected (as shown by the observations), then the logical theory obtained from $\mathit{SD} \cup \mathit{OBS}$ plus the explicit assumption, say $\bigwedge_{c \in \mathit{COMPS}} \neg ab(c)$, that the components are indeed behaving normally, becomes inconsistent.[2] This inconsistency is captured via the *minimal conflict sets*, i.e. those minimal subsets COMPS_0 of *COMPS*, such that $\mathit{SD} \cup \mathit{OBS} \cup \{\bigwedge_{c \in \mathit{COMPS}_0} \neg ab(c)\}$ is still inconsistent. As expected, different notions of minimality can be used at this point. It is common to use the distinguished predicate $ab(\cdot)$ for denoting *abnormal* (or abnormality). So, $ab(c)$ says that component c is abnormal.

On this basis, a *minimal diagnosis* for $\mathcal{M}$ is a minimal subset Δ of COMPS, such that $\mathit{SD} \cup \mathit{OBS} \cup \{\neg ab(c) \mid c \in \mathit{COMPS} \smallsetminus \Delta\} \cup \{ab(c) \mid c \in \Delta\}$ is consistent. That is, consistency is restored by flipping the normality assumption to abnormality for a minimal set of components, and those are the ones considered to be (jointly) faulty. The notion of minimality commonly used is subset-minimality, i.e. a minimal diagnosis must not have a proper subset that is still a diagnosis. We will use this kind of minimality in relation to diagnosis. Diagnosis can be obtained from conflict sets (Reiter 1987). See also (Struss 2008, sec. 10.4) for a broader review of model-based diagnosis.

Diagnostic reasoning is non-monotonic in the sense that a diagnosis may not survive after the addition of new observations (Reiter 1987).

3 Repairs and Causality for Query Answers

Let $D = D^n \cup D^x$ be a database instance for schema $\mathcal{S}$, and $\mathcal{Q} : \exists \bar{x}(P_1(\bar{x}_1) \wedge \cdots \wedge P_m(\bar{x}_m))$ be a boolean conjunctive query (BCQ). Suppose $\mathcal{Q}$ is unexpectedly true in D. Actually, it is expected that $D \not\models \mathcal{Q}$, or equivalently, that $D \models \neg\mathcal{Q}$. Now, $\neg\mathcal{Q}$ is logically equivalent to a formula of the form $\kappa(\mathcal{Q})\colon \forall \bar{x} \neg(P_1(\bar{x}_1) \wedge \cdots \wedge P_m(\bar{x}_m))$, which has the form of a denial constraint. The requirement that $\neg\mathcal{Q}$ holds can be captured by imposing the corresponding DC $\kappa(\mathcal{Q})$ to D.

[2]Here, and as usual, the atom $ab(c)$ expresses that component c is (behaving) abnormal(ly).

Since $D \models \mathcal{Q}$, D is inconsistent wrt. the DC $\kappa(\mathcal{Q})$. Now, repairs for (violations of) DCs are obtained by tuple deletions. Intuitively, tuples that account for violations of $\kappa(\mathcal{Q})$ in D are actual causes for $\mathcal{Q}$. Minimal sets of tuples like this are expected to correspond to S-repairs for D and $\kappa(\mathcal{Q})$. Next we make all this precise.

Given an instance $D = D^n \cup D^x$, a BCQ $\mathcal{Q}$, and a tuple $t \in D$, we consider the class containing the sets of differences between D and those S-repairs that do not contain tuple $t \in D^n$, and are obtained by removing a subset of D^n:

$$\mathcal{DF}(D, D^n, \kappa(\mathcal{Q}), t) \;=\; \{D \smallsetminus D' \mid D' \in \mathit{Srep}(D, \kappa(\mathcal{Q})),\; t \in (D \smallsetminus D') \subseteq D^n\}.$$

Now, $s \in \mathcal{DF}(D, D^n, \kappa(\mathcal{Q}), t)$ can written as $s = s' \cup \{t\}$. From the definition of a S-repair, including its S-minimality, $D \smallsetminus (s' \cup \{t\}) \models \kappa(\mathcal{Q})$, but $D \smallsetminus s' \models \neg\kappa(\mathcal{Q})$, i.e. $D \smallsetminus (s' \cup \{t\}) \not\models \mathcal{Q}$, but $D \smallsetminus s' \models \mathcal{Q}$. So, we obtain that t is an actual cause for $\mathcal{Q}$ with contingency set s'. The following proposition formalizes this result.

Proposition 2. Given an instance $D = D^n \cup D^x$, and a BCQ $\mathcal{Q}$, $t \in D^n$ is an actual cause for $\mathcal{Q}$ iff $\mathcal{DF}(D, D^n, \kappa(\mathcal{Q}), t) \neq \emptyset$. $\square$

The next proposition shows that the responsibility of a tuple can also be determined from $\mathcal{DF}(D, D^n, \kappa(\mathcal{Q}), t)$.

Proposition 3. Given an instance $D = D^n \cup D^x$, a BCQ $\mathcal{Q}$, and $t \in D^n$,

1. If $\mathcal{DF}(D, D^n, \kappa(\mathcal{Q}), t) = \emptyset$, then $\rho(t) = 0$.
2. Otherwise, $\rho(t) = \frac{1}{|s|}$, where $s \in \mathcal{DF}(D, D^n, \kappa(\mathcal{Q}), t)$ and there is no $s' \in \mathcal{DF}(D, D^n, \kappa(\mathcal{Q}), t)$ such that, $|s'| < |s|$. $\square$

Example 3. (ex. 1 cont.) Consider the same instance D and query $\mathcal{Q}$. In this case, the DC $\kappa(\mathcal{Q})$ is, in Datalog notation as a negative rule: $\leftarrow S(x), R(x, y), S(y)$.

Here, $\mathit{Srep}(D, \kappa(\mathcal{Q})) = \{D_1,\ D_2,\ D_3\}$ and $\mathit{Crep}(D, \kappa(\mathcal{Q})) = \{D_1\}$, with $D_1 = \{R(a_4, a_3), R(a_2, a_1), R(a_3, a_3), S(a_4), S(a_2)\}$, $D_2 = \{R(a_2, a_1), S(a_4), S(a_2), S(a_3)\}$, $D_3 = \{R(a_4, a_3), R(a_2, a_1), S(a_2), S(a_3)\}$.

For tuple $R(a_4, a_3)$, $\mathcal{DF}(D, D, \kappa(\mathcal{Q}), R(a_4, a_3)) = \{D \smallsetminus D_2\} = \{\{R(a_4, a_3), R(a_3, a_3)\}\}$. This, together with Propositions 2 and 3, confirms that $R(a_4, a_3)$ is an actual cause, with responsibility $\frac{1}{2}$.

For tuple $S(a_3)$, $\mathcal{DF}(D, D, \kappa(\mathcal{Q}), S(a_3)) = \{D \smallsetminus D_1\} = \{S(a_3)\}$. So, $S(a_3)$ is an actual cause with responsibility 1. Similarly, $R(a_3, a_3)$ is an actual cause with responsibility $\frac{1}{2}$, because $\mathcal{DF}(D, D, \kappa(\mathcal{Q}), R(a_3, a_3)) = \{D \smallsetminus D_2,\ D \smallsetminus D_3\} = \{\{R(a_4, a_3), R(a_3, a_3)\}, \{R(a_3, a_3), S(a_4)\}\}$.

It is easy to verify that $\mathcal{DF}(D,\ D, \kappa(\mathcal{Q}), S(a_2))$ and $\mathcal{DF}(D, D, \kappa(\mathcal{Q}), R(a_2, a_1))$ are empty, because all repairs contain those tuples. This means that they do not participate in the violation of $\kappa(\mathcal{Q})$, or equivalently, they do not contribute to make $\mathcal{Q}$ true. So, $S(a_2)$ and $R(a_2, a_1)$ are not actual causes for $\mathcal{Q}$, confirming the result in Example 1. $\square$

Now, we reduce computation of repairs for inconsistent databases wrt. a denial constraint to corresponding problems for causality.

Consider the database instance D for schema $\mathcal{S}$ and a denial constraint $\kappa: \leftarrow A_1(\bar{x}_1), \ldots, A_n(\bar{x}_n)$, to which a boolean conjunct ive *violation view* $V^\kappa: \exists\bar{x}(A_1(\bar{x}_1) \wedge \cdots \wedge A_n(\bar{x}_n))$ can be associated: D violates (is inconsistent wrt.) κ iff $D \models V^\kappa$.

Intuitively, actual causes for V^κ, together with their contingency sets, account for violations of κ by D. Removing those tuples from D should remove the inconsistency.

Given an inconsistent instance D wrt. κ, we collect all S-minimal contingency sets associated with the actual cause t for V^κ, as follows:

$$\begin{aligned}\mathcal{CT}(D, D^n, V^\kappa, t) \;=\; & \{s \subseteq D^n \mid D \smallsetminus s \models V^\kappa,\\ & D \smallsetminus (s \cup \{t\}) \not\models V^\kappa, \text{ and}\\ & \forall s'' \subsetneqq s,\ D \smallsetminus (s'' \cup \{t\}) \models V^\kappa\}.\end{aligned}$$

Notice that for sets $s \in \mathcal{CT}(D, D^n, V^\kappa, t)$, $t \notin s$. Now consider, $t \in \mathcal{CS}(D, \emptyset, V^\kappa)$, the set of actual causes for V^κ when the entire database is endogenous. From the definition of an actual cause and the S-minimality of sets $s \in \mathcal{CT}(D, D, V^\kappa, t)$, $s'' = s \cup \{t\}$ is an S-minimal set such that $D \smallsetminus s'' \not\models V^\kappa$. So, $D \smallsetminus s''$ is an S-repair for D. We obtain:

Proposition 4. (a) Given an instance D and a DC κ, D is consistent wrt. κ iff $\mathcal{CS}(D, \emptyset, V^\kappa) = \emptyset$. (b) $D' \subseteq D$ is an S-repair for D iff, for every $t \in D \smallsetminus D'$, $t \in \mathcal{CS}(D, \emptyset, V^\kappa)$ and $D \smallsetminus (D' \cup \{t\}) \in \mathcal{CT}(D, D, V^\kappa, t)$. $\square$

Now we establish a connection between most responsible actual causes and C-repairs. For this, we collect the most responsible actual causes for V^κ:

$$\begin{aligned}\mathcal{MRC}(D, V^\kappa) \;=\; & \{t \in D \mid t \in \mathcal{CS}(D, \emptyset, V^\kappa),\\ & \nexists t' \in \mathcal{CS}(D, \emptyset, V^\kappa) \text{ with } \rho(t') > \rho(t)\}.\end{aligned}$$

Proposition 5. For an instance D and denial constraint κ, D' is a C-repair for D wrt. κ iff for each $t \in D \smallsetminus D'$: $t \in \mathcal{MRC}(D, V^\kappa)$ and $D \smallsetminus (D' \cup \{t\}) \in \mathcal{CT}(D, D, V^\kappa, t)$. $\square$

Example 4. Consider $D = \{P(a, b), R(b, c), R(b, b)\}$, and the denial constraint $\kappa\!: \leftarrow P(x, y), R(y, z)$, which prohibits a join between P and R. The corresponding violation view (query) is, $V^\kappa: \exists xyz(P(x, y) \wedge R(y, z))$. Since $D \models V^\kappa$, D is inconsistent wrt. κ.

Here, $\mathcal{CS}(D, \emptyset, V^\kappa) = \{P(a, b), R(b, c), R(b, b)\}$, each of whose members is associated with S-minimal contingency sets: $\mathcal{CT}(D, D, V^\kappa, R(b, c)) = \{\{R(b, b)\}\}$, $\mathcal{CT}(D, D, V^\kappa, R(b, b)) = \{\{R(b, c)\}\}$, and $\mathcal{CT}(D, D, V^\kappa, P(a, b)) = \{\emptyset\}$.

According to Proposition 4, the instance obtained by removing each actual cause for V^κ together with its contingency set forms a S-repair for D. Therefore, $D_1 = D \smallsetminus \{P(a, b)\} = \{R(b, c), R(b, b)\}$ is an S-repair. Notice that the S-minimal contingency set associated to $P(a, b)$ is an empty set. Likewise, $D_2 = D \smallsetminus \{R(b,c), R(b,b)\} = \{P(a,b)\}$ is a S-repair. It is easy to verify that D does not have any S-repair other than D_1 and D_2.

Furthermore, $\mathcal{MRC}(D, V^\kappa) = \{P(a,b)\}$. So, according to Proposition 5, D_1 is also a C-repair for D. $\square$

Given an instance D, a DC κ and a ground atomic query A, the following proposition establishes the relationship between consistent query answers to A wrt. the S-repair semantics and actual cases for the violation view V^κ.

Proposition 6. A ground atomic query A, is consistently true, i.e. $D \models_S A$, iff $A \in D \smallsetminus \mathcal{CS}(D, \emptyset, V^\kappa)$. $\square$

Example 5. Consider $D = \{P(a,b), R(b,c), R(a,d)\}$, the DC $\kappa : \leftarrow P(x,y), R(y,z)$, and the ground atomic query $\mathcal{Q} : R(a,d)$. It is easy to see that $\mathcal{CS}(D, \emptyset, V^\kappa) = \{P(a,b), R(b,c)\}$. Then, according to Proposition 6, $R(a,d)$ is consistently true in D, because $D \smallsetminus \mathcal{CS}(D, \emptyset, V^\kappa) = \{R(a,d)\}$. $\square$

4 Causes for IC violations

We may consider a set Σ of ICs ψ that have violation views V^ψ that become boolean conjunctive queries, e.g. denial constraints. Each of such views has the form $V^\psi : \exists \bar{x}(A_1(\bar{x}_1) \wedge \cdots \wedge A_n(\bar{x}_n))$. When the instance D is inconsistent wrt. Σ, some of these views (queries) get the answer *yes* (they become true), and for each of them there is a set $\mathcal{C}(D, D^n, V^\psi)$ whose elements are of the form $\langle t, \{C_1(t), \ldots, C_m(t)\}\rangle$, where t is a tuple that is an actual cause for V^ψ, together with their contingency sets $C_i(t)$, possibly minimal in some sense. The natural question is whether we can obtain repairs of D wrt. Σ from the sets $\mathcal{C}(D, D^n, V^\psi)$.

In the following we consider the case where $D^n = D$, i.e. we consider the sets $\mathcal{C}(D, D, V^\psi)$, simply denoted $\mathcal{C}(D, V^\psi)$. We recall that $\mathcal{CS}(D, V^\psi)$ denotes the set of actual causes for V^ψ. We denote with $\mathcal{CT}(D, V^\psi, t)$ the set of all subset-minimal contingency sets associated with the actual cause t for V^ψ.

The (naive) Algorithm *SubsetRepairs* that we describe in high-level term in the following accepts as input an instance D, a set of DCs Σ, and the sets $\mathcal{C}(D, V^\psi)$, each of them with elements of the form $\langle t, \{C_1(t), \ldots, C_m(t)\}\rangle$ where each $C_i(t)$ is subset-minimal. The output of the algorithm is $\mathit{Srep}(D, \Sigma)$, the set of S-repairs for D.

The idea of the algorithm is as follows. For each V^ψ, $D \smallsetminus (\{t\} \cup C(t))$ where, $t \in \mathcal{CS}(D, V^\psi)$ and $C(t) \in \mathcal{CT}(D, V^\psi, t)$, is consistent with ψ since, according to the definition of an actual cause, $D \smallsetminus (\{t\} \cup C(t)) \not\models V_\psi$.

Therefore, $D' = D \smallsetminus \bigcup_{\psi \in \Sigma}\{\{t\} \cup C(t) \mid t \in \mathcal{CS}(D, V^\psi)$ and $C(t) \in \mathcal{CT}(D, V^\psi, t)\}$ is consistent with Σ. However, it may not be an S-repair, because some violation views may have common causes.

In order to obtain S-repairs, the algorithm finds common causes for the violation views, and avoids removing redundant tuples to resolve inconsistencies. In this direction, the algorithm forms a set collecting all the actual causes for violation views: $S = \{t \mid \exists \psi \in \Sigma, t \in \mathcal{CS}(D, V^\psi)\}$. It also builds the collection of non-empty sets of actual causes for each violation view: $\mathcal{C} = \{\mathcal{CS}(D, V^\psi) \mid \exists \psi \in \Sigma, \mathcal{CS}(D, V^\psi) \neq \emptyset\}$. Clearly, $\mathcal{C}$ is a collection of subsets of set S.

Next, the algorithm computes the set of all subset-minimal *hitting sets* of the collection C.[3] Intuitively, an S-minimal hitting set of C contains an S-minimal set of actual causes that covers (i.e. intersects) all violation views, i.e. each violation view has an actual cause in the hitting set. The algorithm collects all S-minimal hitting sets of C in $\mathcal{H}$.

Now, for a hitting set $h \in \mathcal{H}$, for each $t \in h$, if t covers V_ψ, the algorithm removes both t and $C(t)$ from D (where $C(t) \in \mathcal{CT}(D, V^\psi, t)$). Since it may happen that a violation view is covered by more than one element in h, the algorithm makes sure that just one of them is chosen. The result is an S-repair for D. The algorithm repeats this procedure for all sets in $\mathcal{H}$. The result is $\mathit{Srep}(D, \Sigma)$.

Example 6. Consider the instance $D = \{P(a,b), R(b,c), S(c,d)\}$, and the set of DCs $\Sigma = \{\psi_1, \psi_2\}$, with $\psi_1 : \leftarrow P(x,y), R(y,z)$, and $\psi_2 : \leftarrow R(x,y), S(y,z)$. The corresponding violation views are $V^{\psi_1} : \exists xyz(P(x,y) \wedge R(y,z))$, and $V^{\psi_2} : \exists xyz(R(x,y) \wedge S(y,z))$.

Here, $\mathcal{C}(D, V^{\psi_1}) = \{\langle P(a,b), \{\emptyset\}\rangle, \langle R(b,c), \{\emptyset\}\rangle\}$, and $\mathcal{C}(D, V^{\psi_2}) = \{\langle R(b,c), \{\emptyset\}\rangle, \langle S(c,d), \{\emptyset\}\rangle\}$.

The set S in the algorithm above, actual causes for ψ_1 or ψ_2, is $S = \{P(a,b),\ R(b,c), S(c,d)\}$. The collection C, of sets of actual causes for ψ_1 and ψ_2, is $C = \{\{P(a,b), R(b,c)\}, \{R(b,c), S(c,d)\}\}$.

The subset-minimal hitting sets for the collection C are: $h_1 = \{R(b,c)\}$, $h_2 = \{S(c,d), P(a,b)\}$. Since the contingency set for each of the actual causes is empty, $D \smallsetminus h_1$ and $D \smallsetminus h_2$ are the S-repairs for D. $\square$

The following theorem states that algorithm *SubsetRepairs* provides a sound and complete method for computing $\mathit{Srep}(D, \Sigma)$.

Theorem 1. Given an instance D, a set Σ of DCs, and the sets $\mathcal{C}(D, V^\psi)$, for $\psi \in \Sigma$, $\mathit{SubsetRepairs}$ computes exactly $\mathit{Srep}(D, \Sigma)$. $\square$

The connection between causality and databases repair provides this opportunity to apply results and techniques developed in each context to the other one. In particular, in our future works we will use this connection to provide some complexity results in the context of consistent query answering.

5 Diagnosis and Query Answer Causality

As before, let $D = D^n \cup D^x$ be a database instance for schema $\mathcal{S}$, and $\mathcal{Q} : \exists \bar{x}(P_1(\bar{x}_1) \wedge \cdots \wedge P_m(\bar{x}_m))$ be BCQ. Assume that $\mathcal{Q}$ is, possibly unexpectedly, true in D. Also

[3] A set $S' \subseteq S$ is a hitting set for $\mathcal{C}$ if, for every $C_i \in \mathcal{C}$, there is a $c \in C_i$ with $c \in S'$. A hitting set is subset-minimal if no proper subset of it is also a hitting set.

as above, the associated DC is $\kappa(\mathcal{Q}): \forall\bar{x}\neg(P_1(\bar{x}_1) \wedge \cdots \wedge P_m(\bar{x}_m))$. So, it holds $D \not\models \kappa(\mathcal{Q})$, i.e. D violates the DC. This is our observation, and we want to find causes for it, using a diagnosis-based approach. Those causes will become causes for $\mathcal{Q}$ being true; and the diagnosis will uniquely determine those causes.

In this direction, for each predicate $P \in \mathcal{P}$, we introduce predicate ab_P, with the same arity as P. Any tuple in its extension is said to be *abnormal* for P. Our "system description", SD, for a diagnosis problem will include, among other elements, the original database, expressed in logical terms, and the DC being true "under normal conditions".

More precisely, we consider the following *diagnosis problem*, $\mathcal{M} = (SD, D^n, \mathcal{Q})$, associated to $\mathcal{Q}$. Here, SD is the FO system description that contains the following elements:

(a) $Th(D)$, which is Reiter's logical reconstruction of D as a FO theory (Reiter 1982).

(b) Sentence $\kappa(\mathcal{Q})^{ext}$, which is $\kappa(\mathcal{Q})$ rewritten as follows:

$$\kappa(\mathcal{Q})^{ext}: \forall\bar{x}\neg(P_1(\bar{x}_1) \wedge \neg ab_{P_1}(\bar{x}_1) \wedge \cdots \wedge P_m(\bar{x}_m) \wedge \neg ab_{P_m}(\bar{x}_m)). \tag{1}$$

(This formula can be refined by applying the abnormality predicate, ab, to endogenous tuples only.)

(c) The inclusion dependencies: $\forall\bar{x}(ab_P(\bar{x}) \rightarrow P(\bar{x}))$.

Now, the last entry in $\mathcal{M}$, $\mathcal{Q}$, is the *observation*, which together with *SD* will produce (see below) and inconsistent theory. This is because in $\mathcal{M}$ we make the initial and explicit assumption that all the abnormality predicates are empty (equivalently, that all tuples are normal), i.e. we consider, for each predicate P, the sentence

$$\forall\bar{x}(ab_P(\bar{x}) \rightarrow \textbf{false}), \tag{2}$$

where, **false** is a propositional atom that is always false. Actually, the second entry in $\mathcal{M}$ tells us how we can restore consistency, namely by (minimally) changing the abnormality condition of tuples in D^n. In other words, the rules (2) are subject to qualifications: some endogenous tuples may be abnormal. Each diagnosis for the diagnosis problem shows a subset-minimal set of endogenous tuples that are abnormal.

Example 7. (ex. 2 cont.) For the instance $D = \{S(a_3), S(a_4), R(a_4, a_3)\}$, with $D^n = \{S(a_4), S(a_3)\}$, consider the diagnostic problem $\mathcal{M} = (SD, \{S(a_4), S(a_3)\}, \mathcal{Q})$, where SD contains the following sentences:

(a) Predicate completion axioms:
$\forall xy(R(x,y) \leftrightarrow x = a_4 \wedge y = a_3)$,
$\forall x(S(x) \leftrightarrow x = a_3 \vee x = a_4)$.

(b) Unique names assumption: $a_4 \neq a_3$.

(c) $\kappa(\mathcal{Q})^{ext}$: $\forall xy\neg(S(x) \wedge \neg ab_S(x) \wedge R(x,y) \wedge \neg ab_R(x,y) \wedge S(y) \wedge \neg ab_S(y))$.

(d) $\forall xy(ab_R(x,y) \rightarrow R(x,y))$, $\forall x(ab_S(x) \rightarrow S(x))$.

The explicit assumption about the normality of all tuples is captured by:

$$\forall xy(ab_R(x,y) \rightarrow \textbf{false}),\ \forall x(ab_S(x) \rightarrow \textbf{false}). \qquad \Box$$

Now, the observation is $\mathcal{Q}$ (is true), obtained by evaluating query $\mathcal{Q}$ on (theory of) D. In this case, $D \not\models \kappa(\mathcal{Q})$. Since all the abnormality predicates are assumed to be empty, $\kappa(\mathcal{Q})$ is equivalent to $\kappa(\mathcal{Q})^{ext}$, which also becomes false wrt D. As a consequence, $SD \cup \{(2)\} \cup \{\mathcal{Q}\}$ is an inconsistent FO theory. Now, a diagnosis is a set of endogenous tuples that, by becoming abnormal, restore consistency.

Definition 1. (a) A *diagnosis* for a diagnosis problem $\mathcal{M}$ is a $\Delta \subseteq D^n$, such that $SD \cup \{ab_P(\bar{c}) \mid P(\bar{c}) \in \Delta\} \cup \{\neg ab_P(\bar{c}) \mid P(\bar{c}) \in D \smallsetminus \Delta\} \cup \{\mathcal{Q}\}$ becomes consistent. (b) $\mathcal{D}(\mathcal{M}, t)$ denotes the set of subset-minimal diagnoses for $\mathcal{M}$ that contain a tuple $t \in D^n$. (c) $\mathcal{MCD}(\mathcal{M}, t)$ denotes the set of diagnoses of $\mathcal{M}$ that contain a tuple $t \in D^n$ and have the minimum cardinality (among those diagnoses that contain t). $\Box$

Clearly, $\mathcal{MCD}(\mathcal{M}, t) \subseteq \mathcal{D}(\mathcal{M}, t)$. The following proposition specifies the relationship between minimal diagnoses for $\mathcal{M}$ and actual causes for $\mathcal{Q}$.

Proposition 7. Consider $D = D^n \cup D^x$, a BCQ $\mathcal{Q}$, and the diagnosis problem $\mathcal{M}$ associated to $\mathcal{Q}$. Tuple $t \in D^n$ is an actual cause for $\mathcal{Q}$ iff $\mathcal{D}(\mathcal{M}, t) \neq \emptyset$. $\Box$

The next proposition tells us that the responsibility of an actual cause t is determined by the cardinality of the diagnoses in $\mathcal{MCD}(\mathcal{M}, t)$.

Proposition 8. Consider $D = D^n \cup D^x$, a BCQ $\mathcal{Q}$, the diagnosis problem $\mathcal{M}$ associated to $\mathcal{Q}$, and a tuple $t \in D^n$.

(a) $\rho(t) = 0$ iff $\mathcal{MCD}(\mathcal{M}, t) = \emptyset$.

(b) Otherwise, $\rho(t) = \frac{1}{|s|}$, where $s \in \mathcal{MCD}(\mathcal{M}, t)$. $\Box$

Example 8. (ex. 7 cont.) The diagnosis problem $\mathcal{M}$ has two diagnosis namely, $\Delta_1 = \{S(a_3)\}$ and $\Delta_4 = \{S(a_4)\}$.

Here, $\mathcal{D}(\mathcal{M}, S(a_3)) = \mathcal{MCD}(\mathcal{M}, S(a_3)) = \{\{S(a_3)\}\}$ and $\mathcal{D}(\mathcal{M}, S(a_4)) = \mathcal{MCD}(\mathcal{M}, S(a_4)) = \{\{ S(a_4)\}\}$. Therefore, according to Proposition 7 and 8, both $S(a_3)$ and $S(a_4)$ are actual cases for $\mathcal{Q}$, with responsibility 1. $\Box$

Notice that the consistency-based approach to causality provided in this section can be considered as a technique for computing repairs for inconsistent databases wrt. denial constraints (it is a corollary of 4 and 8). It is worth mentioning that this approach has been implicitly used before in databases repairing in (Arenas et al. 2003), where the authors introduce *conflict graphs* to characterize S-repairs for inconsistent databases wrt. FDs. We will use this connection in our future work to provide some complexity results in the context of causality.

6 Discussion

Here we discuss some directions of possible or ongoing research.

Open queries. We have limited our discussion to boolean queries. It is possible to extend our work to consider conjunctive queries with free variables, e.g. $\mathcal{Q}(x) : \exists yz(R(x,y) \wedge S(y,z))$. In this case, a query answer would be of the form $\langle a \rangle$, for a a constant, and causes would be found for such an answer. In this case, the associated denial constraint would be of the form $\kappa^{\langle a \rangle} : \leftarrow R(a,y), S(y,z)$, and the rest would be basically as above.

Algorithms and complexity. Given the connection between causes and different kinds of repairs, we might take advantage for causality of algorithms and complexity results obtained for database repairs. This is matter of our ongoing research. In this work, apart from providing a naive algorithm for computing repairs from causes, we have not gone into detailed algorithm or complexity issues. The results we already have in this direction will be left for an extended version of this work.

Endogenous repairs. The partition of a database into endogenous and exogenous tuples has been exploited in the context of causality. However, this kind of partition is also of interest in the context of repairs. Considering that we should have more control on endogenous tuples than on exogenous ones, which may come from external sources, it makes sense to consider *endogenous repairs* that are obtained by updates (of any kind) on endogenous tuples. For example, in the case of violation of denial constraints, endogenous repairs would be obtained -if possible- by deleting endogenous tuples only. If there are no repairs based on endogenous tuples only, a preference condition could be imposed on repairs (Yakout et al. 2011; Staworko, Chomicki, and Marcinkowski 2012), privileging those that change exogenous the least. (Of course, it could also be the other way around, that is we may feel more inclined to change exogenous tuples than our endogenous ones.)

As a further extension, it could be possible to assume that combinations of (only) exogenous tuples never violate the ICs, something that could be checked at upload time. In this sense, there would be a part of the database that is considered to be consistent, while the other is subject to possible repairs. A situation like this has been considered, for other purposes and in a different form, in (Greco, Pijcke, and Wijsen 2014).

Actually, going a bit further, we could even consider the relations in the database with an extra, binary attribute, N, that is used to annotate if a tuple is endogenous or exogenous (it could be both), e.g. a tuple like $R(a,b,yes)$. ICs could be annotated too, e.g. the "exogenous" version of DC κ, could be $\kappa^E : \leftarrow P(x,y,yes), R(y,z,yes)$, and could be assumed to be satisfied.

ASP specification of causes. Above we have presented a connection between causes and repairs. S-repairs can be specified by means of answer set programs (ASPs) (Arenas, Bertossi, and Chomicki 2003; Barcelo, and Bertossi 2002; Barcelo, Bertossi, and Bravo 2003), and C-repairs too, with the use of weak program constraints (Arenas, Bertossi, and Chomicki 2003). This should allow for the introduction of ASPs in the context of causality, for specification and reasoning. There are also ASP-based specifications of diagnosis (Eiter et al. 1999) that could be brought into a more complete picture.

Causes and functional dependencies. Functional dependencies (FDs), that can be considered as denial constraints, have violation views that are conjunctive, but contain inequalities. They are still monotonic views though. Much has been done in the area of repairs and consistent query answering (Bertossi 2011). On the other side, in causality only conjunctive queries without built-ins have been considered (Meliou et al. 2010a). It is possible that causality can be extended to conjunctive queries with built-ins through the repair connection; and also to non-conjunctive queries via repairs wrt. more complex integrity constraints.

View updates. Another venue to explore for fruitful connections relates to the *view update problem*, which is about updating a database through views. This old and important problem in databases has also been treated from the point of view of abductive reasoning (Kakas, and Mancarella 1990; Console, Sapino, and Theseider-Dupre 1995).[4] User knowledge imposed through view updates creates or reflects *uncertainty* about the base data, because alternative base instances may give an account of the intended view updates.

The view update problem, specially in its particular form of of *deletion propagation*, has been recently related in (Kimelfeld 2012; Kimelfeld, Vondrak, and Williams 2012) to causality as introduced in (Meliou et al. 2010a).[5]

Database repairs are also related to the view update problem. Actually, *answer set programs* (ASP) for database repairs (Barcelo, Bertossi, and Bravo 2003) implicity repair the database by updating intentional, annotated predicates.

Even more, in (Bertossi, and Li 2013), in order to protect sensitive information, databases are explicitly and virtually "repaired" through secrecy views that specify the information that has to be kept secret. In order to protect information, a user is allowed to interact only with the virtually repaired versions of the original database that result from making those views empty or contain only null values. Repairs are specified and computed using ASP, and in (Bertossi, and Li 2013) an explicit connection to prioritized attribute-based repairs (Bertossi 2011) is made.

7 Conclusions

In this work, we have uncovered the relationships between causality in databases, database repairs, and consistency-based reasoning, as three forms of non-monotonic reasoning. Establishing the connection between these problems allows us to apply results and techniques developed for each of them to the others. This should be particularly beneficial for causality in databases, where still a limited number of results and techniques have been obtained or developed. This becomes matter of our ongoing and future research.

[4] Abduction has also been explicitly applied to database repairs (Arieli et al. 2004).

[5] Notice only tuple deletions are used with violation views and repairs associated to denial constraints.

Our work suggests that diagnostic reasoning, as a form of non-monotonic reasoning, can provide a solid theoretical foundation for query answer explanation and provenance. The need for such foundation and the possibility of using non-monotonic logic for this purpose are mentioned in (Cheney et al. 2009; Cheney 2011).

Acknowledgments: Research funded by NSERC Discovery, and the NSERC Strategic Network on Business Intelligence (BIN). L. Bertossi is a Faculty Fellow of IBM CAS. Conversations on causality in databases with Alexandra Meliou during Leo Bertossi's visit to U. of Washington in 2011 are much appreciated. He is also grateful to Dan Suciu and Wolfgang Gatterbauer for their hospitality. Leo Bertossi is also grateful to Benny Kimelfeld for stimulating conversations at LogicBlox, and pointing out to (Kimelfeld 2012; Kimelfeld, Vondrak, and Williams 2012).

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