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Immutably Answering Why-Not Questions for Equivalent Conjunctive Queries

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Abstract

Answering Why-Not questions consists in explaining to developers of complex data transformations or manipulations why their data transformation did not produce some specific results, although they expected them to do so. Different types of explanations that serve as Why-Not answers have been proposed in the past and are either based on the available data, the query tree, or both. Solutions (partially) based on the query tree are generally more efficient and easier to interpret by developers than solutions solely based on data. However, algorithms producing such query-based explanations so far may return different results for reordered conjunctive query trees, and even worse, these results may be incomplete. Clearly, this represents a significant usability problem, as the explanations developers get may be partial and developers have to worry about the query tree representation of their query, losing the advantage of using a declarative query language. As remedy to this problem, we propose the Ted algorithm that produces the same complete query-based explanations for reordered conjunctive query trees.

Categories and Subject Descriptors H.4 [Information Systems Applications]: Miscellaneous; D.2 [Software Engineering]: Testing and Debugging

Keywords data provenance, query analysis

1. Introduction

The increasing load of data produced nowadays is coupled with an increasing need for complex data transformations that developers design to process these data in every-day tasks, such as data cleaning or data enrichment. These transformations, commonly specified declaratively, may result in unexpected outcomes. For instance, given the query and data of Fig. 1, a developer (or scientist) may wonder why the planet Kepler78b is missing from the result, even though he expected or intended it to be part of it. Traditionally, he would repeatedly manually analyze the query to identify a possible reason, fix it, and test it to check whether the missing answer is now present or if other problems need to be fixed.

To help developers during query analysis and debugging, and in particular for answering why-not questions as the one used in the above example that asks why some data are not part of a result, different algorithms have recently been proposed for relational and SQL queries [2, 3, 6–8] as well as other types of queries (top-k [5], reverse skyline queries [10]). In this paper, we focus on relational queries, for which existing algorithms explain a missing-answer either based on the data (instance-based explanations), the query (query-based explanations), or both (hybrid explanations). Moreover, we focus on solutions producing query-based explanations, as these are generally more efficient while providing sufficient information for query analysis and debugging. Taking a closer look at existing methods, we notice that these return different explanations for reordered query trees. This is due to the fact that these algorithms reason at the level of query tree operators and trace data provenance, through one particular instance of a query tree. On this particular query tree, they identify at which picky operators compatible data are lost, and output these.

Example 1.1. Consider the SQL query Q and data D of Fig. 1 and assume that a developer wants an explanation for the absence of the planet Kepler78b in the result Q(D), knowing that this planet does not revolve around the Sun. So here, the why-not question is “Why is tuple (Planet:Kepler78b, Star:Sun) not in D?” Fig. 2 shows two possible query trees for Q. It also shows the picky operators that Why-Not [3] (●) and NedExplain [2] (★) return as query-based explanations as well as query operators returned as part of hybrid explanations by Conseil [6] (●). It is easy to see that each algorithm returns a different result for each of the two query trees, and in most cases, it is only a partial result as the true explanation of the missing answer is that both the selection is too strict for the compatible tuple (Kepler78b, 1.7, NULL) from table Planet and this tuple does not find any join partner in table Star.
To more accurately answer Why-Not questions, we propose the Ted algorithm that identifies all the picky operators of a relational query and explains how they prevent the generation of the desired answer. The proposed explanations take the form of a polynomial, similarly to provenance semi-rings for how-provenance [4] that explain data that exists in a query result. The main asset of this algorithm is that the computed set of query-based explanations that are invariant for reordered query trees for conjunctive queries (Sec. 2). We then present Ted, a first algorithm computing such explanations and discuss preliminary experiments (Sec. 3). Sec. 4 concludes and discusses future work.

2. Polynomial-Based Why-Not answers

We assume that the reader is familiar with the relational model and tableau theory [1]. Here, we briefly revisit necessary notions of previously defined Why-Not questions in Sec. 2.1. Sec. 2.2 reviews tableaux theory [1]. Here, we briefly revisit necessary notions of relations \( R \) and the database instance \( I \) in Fig. 3(a).

We use a unique annotation \( Id \) to identify a tuple of \( T \). Further consider the relational query in Fig. 3(b). The query result includes the tuple \( \{ R.B:5, S.C:9, T.D:A \} \).

2.1 The Why-Not Question

Given a query \( Q \) over a database schema \( S_Q \) and an input instance \( I \), a developer formulates a Why-Not question as a predicate \( P \) that is a disjunction of conditional tuples (c-tuples) [9]. A full definition is available in [2]. Next, we will concentrate on conjunctive queries only and predicates composed of a single c-tuple. The proposed method trivially extends to unions of conjunctive queries and a general predicate \( P \), but we omit a discussion for space constraints.

A c-tuple \( t_c \) has the form \( (t_c, \text{cond}) \), where \( t_c \) is a tuple with attribute values being variables and \( \text{cond} = \bigwedge_{i=1}^m \text{pred}_i \) is a conjunction of atomic conditions s.t. each \( \text{pred}_i \) is a comparison between a variable and a constant, or a comparison between two variables. In the following, we will concentrate on the condition associated with a c-tuple \( t_c \) as \( t_c.\text{cond} \) and the set of variables referred to in \( t_c \) as \( \text{var}(t_c)^2 \). Special attention has to be given to the condition associated with the c-tuple \( t_c \). More specifically, we distinguish here between simple and complex conditions.

\( S_Q \) is the query schema of \( Q \) as defined in [2], which implies that each relation schema in \( S_Q \) occurs only once in \( Q \).

We also use \( \text{var}(\cdot) \) to retrieve the set of variables from other structures, e.g., \( \text{var}(t_c.\text{cond}) \) returns the variables for which constraints are specified.

Notation 2.1. \textbf{(Simple/Complex condition/c-tuple)} An atomic condition \( \text{pred}_i \) in a condition \( \text{cond} \) is simple if it compares (a) a variable with a constant or (b) two variables referring to source attributes of the same relation. Otherwise, it is a complex atomic condition. We qualify \( \text{cond} \) as complex if it includes at least one complex atomic condition, and simple otherwise. Finally, a c-tuple is simple if its condition \( \text{cond} \) is simple, and complex otherwise.

Example 2.2. Given the scenario of Ex. 2.1, we wonder why there is not a result tuple, s.t. the value of \( R.B \) is smaller than the one of \( T.D \) and on the same time the value of \( S.C \) smaller or equal to 9. This Why-Not question is expressed by \( t_c.\text{cond} = (R.B \leq T.D \wedge S.C < 9) \). In \( t_c.\text{cond} \), \( z < 9 \) is a simple condition whereas \( x < y \) is a complex condition, because the variables \( x \) and \( y \) refer to different relations (\( R \) and \( T \), respectively).

Consequently, \( t_c \) is a complex c-tuple.

2.2 Compatible Data

Intuitively, compatible data designates any source tuples that could have provided data to form the missing answer modelled by \( t_c \). The first step towards answering the Why-Not question consists in identifying these source tuples and more specifically their combinations that form the missing answer in the absence of restrictions in \( Q \). In a second step, discussed in the next section, we will identify query conditions (query operators) that prune these tuple combinations.

Example 2.3. Continuing Ex. 2.2, \( t_c.\text{cond} \) implies that the missing-answer is based on a source tuple \( t_s \in I_R \), a source tuple \( t_s \in I_S \) for which \( t_s.(R.B) < t_y.(T.D) \) and \( t_s.(S.C) \leq 9 \). Due to the complex condition, \( t_s \) and \( t_y \) need to be chosen in correlation with one another, whereas \( t_s \) is independent from all others. We obtain \( (Id_1, Id_9), (Id_1, Id_{10}) \) and \( (Id_2, Id_{10}) \) as compatible tuple concatenation for correlated \( (t_s, t_y) \), while for \( t_s \) each one of the tuples in \( S \), i.e., \( Id_5, \ldots, Id_8 \) comprises a compatible tuple concatenation.

Previous approaches [2, 3] consider all compatible tuples independently from each other, e.g., they consider both \( Id_1 \) and \( Id_2 \) as compatible for \( t_c \). However, \( Id_2 \) should lose this property when \( Id_1 \) is chosen for \( t_y \), a fact previously ignored. Therefore, in this paper, we introduce the compatibility of a tuple concatenation rather than compatibility on isolated tuples. According to our definition, each concatenated compatible tuple (cc-tuple) would have resulted in the missing-answer if it was not pruned by some query operators.

Tableau skeleton. We first define a tableau skeleton \( T_{S_Q} \), which is a set of variable tuples, one for each relation schema in \( S_Q \), such that a variable is not used twice in \( T_{S_Q} \). The relations in \( S_Q \) are also used to identify the rows of \( T_{S_Q} \), as shown in Tab. 1.

<table>
<thead>
<tr>
<th>R.A</th>
<th>R.B</th>
<th>T.C</th>
<th>T.D</th>
<th>T.E</th>
<th>S.B</th>
<th>S.C</th>
<th>S.D</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>x1</td>
<td>x2</td>
<td>x3</td>
<td>x4</td>
<td>x5</td>
<td>x6</td>
<td>x7</td>
</tr>
</tbody>
</table>

Table 1. Tableau skeleton \( T_{S_Q} \)

Mappings. Our subsequent definitions require the mapping functions described and illustrated in Tab. 2. Note that \( h_{\text{var}}(t_c) \) is used to rename the variables \( \text{var}(t_c) \) of \( t_c \) into variables in \( T_{S_Q} \). Both functions \( h_3 \) and \( h_{\text{var}}(\cdot) \) are extended to apply on the tableau and the c-tuple conditions respectively. Finally, \( f \) naturally extends to concatenated tuples, e.g., \( f(Id_1, Id_9) = (R.A:1, R.B:3; S.B:3, S.C:4, S.D:5) \).
Compatible concatenated tuples. We are now ready to define cc-tuples. To this end, we enrich $T_{SQ}$ by the condition of $\text{cond} = h_{\text{var}(t_c)}(t_c, \text{cond})$ and a summary $S_t_c = h_{\text{var}(t_c)}(\text{var}(t_c, t_v))$. We thus obtain the compatibility tableau $T_{tc} = (S_t_c, T_{SQ}, \text{cond})$. For brevity, we will also use the notation $T_{t_c} = (T_{SQ}, \text{cond})$ (omitting the summary). A sub-condition $R.\text{cond}$ can be associated with row $R$ of $T_{tc}$ by restricting the conjunction $\text{cond}$ to predicates $\text{pred}_R$ sharing variables with $\text{var}(R)$. So, given $T_{SQ}$ in Tab. 1 and the condition $\text{cond} = (x_2 < x_4 \land x_7 \leq 9)$, we obtain $T_{t_c}$ in Tab. 3 (ignore the grouping of the rows for now).

<table>
<thead>
<tr>
<th>Function</th>
<th>Purpose</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h_A : A \to \text{var}(T_{SQ})$</td>
<td>Notation for the mapping between attribute names and variables in $T_{SQ}$.</td>
<td>$h_A(R.A) = x_4$, $h_A^{-1}(x_1) = R.A$</td>
</tr>
<tr>
<td>$h_{\text{var}(t_c)} : \text{var}(t_c) \to \text{var}(T_{SQ})$</td>
<td>Maps variables of $t_c$ to variables of $T_{SQ}$ associated to the same relation attribute.</td>
<td>$h_{\text{var}(t_c)}(x) = x_3$, $h_{\text{var}(t_c)}(y) = x_4$, $h_{\text{var}(t_c)}(z) = x_7$</td>
</tr>
<tr>
<td>$f : ID \to I$</td>
<td>Maps a tuple annotation to the actual tuple.</td>
<td>$f(t_{Id}) = (R.A : 1, R.B : 4)$</td>
</tr>
</tbody>
</table>

Table 2. Mapping functions

Example 2.6. First, focus on $t_1$ and the first row $R$ of Tab. 4. The atomic condition $x_1 = 1$ in $\text{cond}_{t_1,R}$ contradicts the atomic condition $x_1 \geq 3$ of $\text{cond}_{SQ,R}$. Thus, we say that $x_1 > 3$ is a picky condition. The atomic conditions on $x_2$ in $\text{cond}_{t_1,R}$ and $\text{cond}_{SQ,R}$ are simultaneously satisfied, since $x_2 = 3 \land x_2 = 3 \land x_2 = x_6$ is true.

In the same way, we identify in the rest of the rows the picky atomic conditions and eventually obtain the set of picky atomic conditions w.r.t. $\tau_1 : \{x_1 > 3, x_7 \geq 8, x_4 = x_6\}$. Associating these conditions to their respective query operators (see Fig. 3), we obtain the set of picky operators $\{\text{op}_2, \text{op}_3, \text{op}_4\}$.

Notation 2.2. (Picky operators w.r.t. $\tau$). We define the set of picky conditions $\tau$ as $\text{PC}_\tau = \{c | c \in \text{cond}_{SQ} \text{ and } c \notin \tau\}$. Each atomic condition $c$ is associated with a query operator $\text{op}_c$ in $Q$, and we define the set of picky operators $\tau$ as $\text{PO}_\tau = (\text{op})_{\text{op}_c \text{ associated with some } c \in \text{PC}_\tau}$.

The complete Why-Not answer includes an explanation for the pruning of each cc-tuple $\tau \in \text{CCT}(T_{t_c}, I)$ and takes the form of a polynomial of query operators.

**Definition 2.2.** (Why-Not answer w.r.t. $t_c$.) Given query $Q$ over a database schema $S_{SQ}$, the instance $I$ over $S_{SQ}$, and the compatibility tableau $T_{tc}$ associated with the Why-Not question $t_c$, we define the Why-Not answer w.r.t. $t_c$ as

$$\text{PO}_{\text{CCT}(T_{t_c}, I) \text{ op}_{\text{PC}_\tau}}$$

We justify modeling each $\text{PO}_c$ with a product by the fact that in order for $\tau$ to ‘survive’ up to the query result, every single picky operator w.r.t. $\tau$ must be ‘repaired’. The sum of the products of each $\tau \in \text{CCT}(T_{t_c}, I)$ stems from the fact that, if any addend is ‘correctly repaired’, the associated $\tau$ will return the missing answer.

Example 2.7. In Ex. 2.6 we found that $\{\text{op}_2, \text{op}_3, \text{op}_4\}$ are the picky operators for $\tau_1$, which results in the addend $\text{op}_2 \ast \text{op}_4 \ast \text{op}_5$. Applying the same for all 12 cc-tuples in our example, we obtain the final result $\text{op}_2 \ast \text{op}_3 \ast \text{op}_4 \ast 3 \ast \text{op}_2 \ast \text{op}_5 \ast 3 \ast \text{op}_4 \ast \text{op}_1 \ast \text{op}_5 \ast \text{op}_3 \ast \text{op}_4 \ast \text{op}_2 \ast \text{op}_4 \ast 2 \ast \text{op}_2 \ast \text{op}_4 \ast 2 \ast \text{op}_3 \ast \text{op}_5$.

**3. The Ted Algorithm**

Alg. 1 presents the Ted algorithm that computes the Why-Not answer defined in Sec. 2 for a conjunctive query $Q$. Ted trivially extends to unions of conjunctive queries and a Why-Not question in form of a disjunction of c-tuples (see Sec. 2.1), however, details are omitted due to space constraints.

Ted starts by a preprocessing phase, that consists in creating the tableau skeleton $T_{SQ}$ and the tableau $T_{t_c}$ (lines 2 and 3). Then, it determines the set of cc-tuples $\text{CCT}(T_{t_c}, I)$ in line 5 before it computes the Why-Not answer (lines 6 – 8). As the computation of the Why-Not answer directly follows from the definitions of Sec. 2.3, we focus our discussion computing $\text{CCT}(T_{t_c}, I)$.

To compute the set of all cc-tuples, we could form the cross product of all relations of $T_{t_c}$ (e.g., $R \times T \times S$) and then verify whether each resulting concatenated tuple $(Id_{Id} Id_{Id})$ satisfies the condition $t_c, \text{cond}$. However, this will result in checking the same conditions numerous times, e.g., the condition $x_7 \leq 9$ will not be checked once for every tuple in relation $S$, but as many times as there are tuples in the cross product. To improve efficiency, we divide the problem into independent subproblems based on a partitioning of the rows in $T_{t_c}$.
4. Outlook and Future Work

Ted is an algorithm that returns query based-explanations for a Why-Not question over a conjunctive query. Opposed to previous work, it is the first algorithm that is guaranteed to return the same explanations, no matter the considered query plan representation. Another novelty is to represent the Why-Not answer as a polynomial. This polynomial has the benefit of being an elegant formalism that can subsequently be used for further processing, e.g., for ranking the importance of “misbehaving” query operators in the query, for actually computing query rewritings that automatically fix the problem, estimating the minimum number of side-effects of a rewriting, etc. These are interesting problems we plan to address in the future. However, before developing solutions to these interesting problems, we will tackle the problem of efficiency. Besides parallel computations, we may for instance reduce the overall complexity by only selecting a “representative” sample of cc-tuples and compute an approximate result (within certain error bounds).

References


