Answer-Set Programs for Repair Updates and Counterfactual Interventions

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Abstract. We briefly describe -mainly through very simple examples-different kinds of answer-set programs with annotations that have been proposed for specifying: database repairs and consistent query answering; secrecy view and query evaluation with them; counterfactual interventions for causality in databases; and counterfactual-based explanations in machine learning.

Repair Programs and Consistent Query Answering. When a relational database fails to satisfy a given set of integrity constraints (ICs) and one wants to obtain semantically correct query answers, one can specify and simultaneously query virtually repaired, i.e. consistent, versions of the database. The so obtained certain answers are considered to be the consistent answers [1, 5]. Answer-set programs (ASPs) with annotations can be used for this task [4, 17]. The motivation for this approach comes from earlier work where annotated predicate logic, a form of multi-valued logic extended with non-monotonic negation, that was used for this task [2].

Example 1. The following is a denial constraint (DC), i.e. it prohibits combinations or joins of database atoms: $\kappa: \neg \exists x \exists y (S(x) \land R(x, y) \land S(y))$. The following database instance $D$ violates $\kappa$.

| R | A | B | S | A |
|---|---|---|---|---|
| $\iota_1$ | $a_4$ | $a_3$ | $\iota_4$ | $a_4$ |
| $\iota_2$ | $a_2$ | $a_1$ | $\iota_5$ | $a_2$ |
| $\iota_3$ | $a_3$ | $a_3$ | $\iota_6$ | $a_2$ |

We use global tuple identifiers (tids) to refer to individual tuples. They appear in predicates’ first arguments followed by a semicolon.

Subset-repairs (S-repairs) of $D$ are consistent w.r.t. $\kappa$, and minimally differ from $D$ under set inclusion. They are: $D_1 = \{R(\iota_1; a_4, a_3), R(\iota_2; a_2, a_1), R(\iota_3; a_3, a_3), S(\iota_4; a_4), S(\iota_5; a_2), S(\iota_6; a_3)\}$, $D_2 = \{R(\iota_2; a_2, a_1), S(\iota_4; a_4), S(\iota_5; a_2), S(\iota_6; a_3)\}$, and $D_3 = \{R(\iota_1; a_4, a_3), R(\iota_2; a_2, a_1), S(\iota_5; a_2), S(\iota_6; a_3)\}$.

The repair program contains the atoms in $D$, and the rules:

$S'(t_1; x, d) \lor R'(t_2; x, y, d) \lor S'(t_3; y, d) \leftarrow S(t_1; x), R(t_2; x, y), S(t_3; y)$.

$S'(t; x, s) \leftarrow S(t; x), \text{not } S'(t; x, d)$.

$R'(t; x, y, s) \leftarrow R(t; x, y), \text{not } R'(t; x, y, d)$.

Here, $t_1, \ldots, t, x, y, \ldots$ are variables, but the annotation $d$ is a constant indicating that the tuple is deleted from $D$. Annotation constant $s$ indicates that the tuple stays in the repair. Here, the first rule captures in its body (i.e. antecedent) a violation of $\kappa$, and the head (i.e. the consequent) offers the alternative tuple deletions that can solve the violation. The last two rules specify that repairs

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keep the original tuples that have not been deleted. Predicates \( R' \) and \( S' \) are nicknames for \( R \) and \( S \), with an extra argument for the annotation.

This repair-program has three stable models, with repair \( D_1 \) corresponding to the model \( M_1 = \{R'(t_1; a_4, a_3, s), R'(t_2; a_2, a_1, s), R'(t_3; a_3, a_3, s), S'(t_4; a_4, s), S'(t_5; a_2, s), S'(t_6; a_3, d)\} \cup D \), in the sense that \( D_1 \) can be read off from \( M_1 \) by keeping only the tuples annotated with \( s \).

If there are interacting ICs, for which repair actions for one of them may affect satisfaction of another one, it is necessary to use a couple of extra annotations to capture a transition process \[7\]. Doing CQA becomes skeptical (or certain) if we can keep the original tuples that have not been deleted. Predicates \( R' \) and \( S' \) are nicknames for \( R \) and \( S \), with an extra argument for the annotation.

Example 2. (example \[1\] cont.) Consider the same database \( D \), and \( V_{\kappa}(x, y) : S(x) \land R(x, y) \land S(y) \) defining the view whose contents we want to hide from users. In order to do this, we repair w.r.t. the associated DC \( \kappa \) by “minimally” changing attribute values by a constant \textsc{NULL}. Since it behaves as in SQL, it cannot be used to satisfy a join. There are two repairs.

\[
\begin{array}{ccc|ccc}
R & A & B & S & A & S \\
\hline
1 & a_4 & a_3 & \bar{t}_4 & a_4 & \bar{t}_4 \\
2 & a_2 & a_1 & \bar{t}_5 & a_2 & \bar{t}_5 \\
3 & a_3 & a_3 & \text{NULL} & a_3 & \text{NULL} \\
\end{array}
\]

In each of them \textsc{NULL} is preventing the satisfaction of a join in \( V_{\kappa} \). In both cases, the set of value changes is minimal under set inclusion.

A program rule that achieves this result is: \( S'(t_1; \text{NULL}) \lor R'(t_2; \text{NULL}, y) \lor R'(t_2; x, \text{NULL}) \lor S'(t_3; \text{NULL}) \leftarrow S(t_1, x), R(t_2, x, y), S(t_3, y) \). \( \Box \)
Counterfactual Programs for Causality in Databases. In [24], actual causality was applied to define and compute database tuples that are causes for a query to be true. Furthermore, causal responsibility was used to assign numerical scores to causes, to reflect their strength as such. A detailed analysis of causality in databases was carried out in [8], where a useful connection with database repairs was unveiled. As consequence, repair program can be used to specify and compute causes.[9]

Example 3. (example 1 cont.) With the same database $D$, the query $Q_\kappa$: $\exists x \exists y(S(x) \land R(x, y) \land S(y))$ is true in $D$. Tuple $t_6$ is a counterfactual cause for $Q_\kappa$ in $D$, in the sense that if $t_6$ is removed from $D$, $Q_\kappa$ is no longer true. Its responsibility is 1, the highest possible. Tuple $t_1$ is an actual cause since deleting it from $D$ together with its contingent tuple $t_3$ makes the query false. Its responsibility is $\frac{1}{1+1} = \frac{1}{2}$, with $I$ the smallest set of its contingent tuples. Similarly, $t_3$ and $t_4$ are actual causes, with responsibility $\frac{1}{2}$.

When $Q_\kappa$ is true, equivalently the IC $\kappa$ is false, in order to obtain causes, tuples have to be deleted from $D$, for which a repair program for $\kappa$ can be used. Causes’ tids can be retrieved by means of the rules: $Cause(t) \leftarrow R(t, x, y, d)$ and $Cause(t) \leftarrow S(t, x, d)$. In order to obtain their contingency tuples, one can use, e.g. $Cont(t, t') \leftarrow R(t, x, y, d), R(t', u, v, d), t \neq t'$, collecting tids that have to be deleted together with $t$. Using set-building and aggregations, one can compute contingency sets and their cardinalities and then, also responsibilities. With WCs one can concentrate on minimum cardinality contingency sets.

Counterfactual Programs for Explainable ML. Consider entity records represented by atomic formulas $E(t; \bar{e}, o)$, with an id $t$, a sequence of feature values $\bar{e}$, and an annotation $o$ for “original record”. They are labeled, say with 0 or 1, by a black-box or open-box classifier represented by a predicate $Cl(t, \ell)$: record with id $t$ received label $\ell$. A particular entity $E(t; \bar{e}, o)$ receives label 1, i.e. $Cl(t, 1)$ is true, and we want to explain this by counterfactually intervening $\bar{e}$, changing feature values, trying to obtain label 0. For each feature we do this, but value changes for other features may be necessary (as with actual causality above). A responsibility score can be assigned to each feature value that depends on the additional required changes (similar but much more general than causal responsibility above) [10] [11]. These are also called score-based attributive or contrastive explanations in explainable AI.

The process of iteratively intervening an entity until it switches label can be specified by means of counterfactual ASPs [12] [13]. For the gist, we give some of the rules in such a program. Since an entity may go through an iteration of feature value changes, we need an annotation, $\star$, to indicate it is in transition, with the rules: $E(e; \bar{x}; \star) \leftarrow E(e; \bar{x}; o)$ and $E(e; \bar{x}; \star) \leftarrow E(e; \bar{x}; do)$, where annotation do indicates a single counterfactual change.

The main rule, $E(t; x'_1, x_2, \ldots, x_n; do) \lor \ldots \lor E(t; x_1, x_2, \ldots, x'_n; do) \leftarrow E(t; \bar{x}; \star), Cl[t; 1], Dom_1(x'_1), \ldots, Dom_n(x'_n), x'_1 \neq x_1, \ldots, x'_n \neq x_n, choice(\bar{x}; x'_1), \ldots, choice(\bar{x}; x'_n)$, specifies that while the label is not switched, a single feature value is non-deterministically replaced by a new one from the feature do-
main. One eventually stops when the label has been switched: $E(t; \bar{x}; s) \leftarrow E(t; \bar{x}; do), C(t, 0)$.

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