Consistent Query Answering via SAT Solving

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The Relational Data Model

- Relational Database: A collection $(R_1, \cdots, R_m)$ of finite relations (tables)
- Relational Query Languages
  - Relational Calculus: (Safe) First-Order Logic
  - SQL: The standard commercial database query language based on relational calculus

Conjunctive Queries

A Conjunctive Query (CQ) is a query specified by a first-order formula of the form

$$\exists y_1, \cdots, \exists y_m\, \varphi(x_1, \cdots, x_n, y_1, \cdots, y_m)$$

where $\varphi(x_1, \cdots, x_n, y_1, \cdots, y_m)$ is a conjunction of atoms.

Example

Schema: $Enrolls(student, course)$, $Teaches(professor, course)$

Query in relational calculus:

$\textsc{Taught-By}(x_1, x_2) : \exists y \big(Enrolls(x_1, y) \wedge Teaches(x_2, y) \big)$

SQL expression for TAUGHT-BY:

SELECT *Enrolls.student*, *Teaches.professor*
FROM *Enrolls, Teaches*
WHERE *Enrolls.course = Teaches.course*

Integrity Constraints and Inconsistent Databases

Key Constraint $R : X \rightarrow Y$,
If two tuples in R agree on X, then they also agree on Y, where Y is the set of attributes of R that are not in X.

Inconsistent Database: A database $\mathcal{I}$ that violates Σ.

- Inconsistencies are unavoidable in the real world

Example

S : $Employees(\underline{EmpID}, Name, Role, Salary)$

$\Sigma : EmpID \rightarrow Name, Role, Salary$

#	<u>*EmpID*</u>	*Name*	*Role*	*Salary*
1	111	Bob Williams	Software Engineer	$90,000
2	112	John Smith	Software Engineer	$100,000
3	112	Alice Brown	Software Intern	$50,000

Coping with Inconsistent Databases

Two different approaches:

- Data Cleaning: Inconsistencies are removed by modifying (adding, deleting, updating) the tuples in the relations.
  - Main approach in the industry
  - More engineering than science

Coping with Inconsistent Databases

Two different approaches:

- Data Cleaning: Inconsistencies are removed by modifying (adding, deleting, updating) the tuples in the relations.
  - Main approach in the industry
  - More engineering than science
- Database Repairs: A principled framework for coping with inconsistent databases without “cleaning” dirty data.

Database Repairs and Consistent Answers

Definition (Arenas, Bertossi, Chomicki – 1999)

Σ a set of integrity constraints and $\mathcal{I}$ an inconsistent database.
Database instance $\mathcal{J}$ is a subset-repair of $\mathcal{I}$ w.r.t. Σ if

- $\mathcal{J} \subset \mathcal{I}$
- $\mathcal{J} \models \Sigma$ (i.e., $\mathcal{J}$ is consistent)
- there is no $\mathcal{J}'$ such that $\mathcal{J}' \models \Sigma$ and $\mathcal{J} \subset \mathcal{J}' \subset \mathcal{I}$.

Definition (Arenas, Bertossi, Chomicki - 1999)

Σ a set of integrity constraints, q a query, and $\mathcal{I}$ an inconsistent database. The consistent answers to q on $\mathcal{I}$ w.r.t. Σ is the set

$$\textsc{Cons}(q, \mathcal{I}, \Sigma) = \bigcap \ \{q(\mathcal{J}) : \mathcal{J} \text{ is a repair of } \mathcal{I} \text{ w.r.t. } \Sigma\}.$$

Database Repairs and Consistent Answers

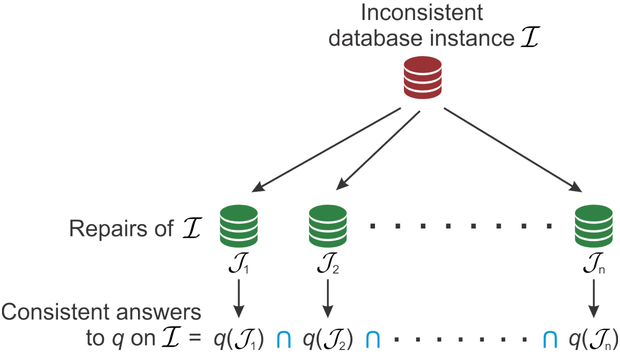

Figure: $\textsc{Cons}(q, \mathcal{I}, \Sigma)$

Consistent Query Answering (CQA)

- Consistent Query Answering (CQA): The problem of computing $\textsc{Cons}(q, \mathcal{I}, \Sigma)$
- CQA is often studied for Conjunctive Queries
- CQA for conjunctive queries can be intractable

Example

$\mathbf{S} : R(\underline{A}, B)$ $\qquad \Sigma : A \rightarrow B$

$\mathcal{I} =$

#	$\underline{A}$	B
1	a_1	b_1
2	a_1	b_2
3	a_2	b_1
4	a_2	b_2

- Four (subset) repairs of $\mathcal{I}$ are $\{1, 3\}, \{1, 4\}, \{2, 3\}$, and $\{2, 4\}$
- Exponentially many repairs, in general

More on the Complexity of CQA

- Boolean CQs: Conjunctive queries with no free variables.
- The decision problem $\textsc{Certainty}(q, \Sigma)$ asks:
  Given a database $\mathcal{I}$, is $\textsc{Cons}(q, \mathcal{I}, \Sigma)$ true?

Example

S : $R(\underline{A}, B),\ S(\underline{C}, D)$ $\qquad$ $\Sigma : A \to B,\ \ C \to D$

- $\textsc{Path}()$: $\exists x, y, z(R(\underline{x}, y) \land S(\underline{y}, z))$
  $\textsc{Certainty}(\textsc{Path})$ is SQL-rewritable.
- $\textsc{Circle}()$: $\exists x, y(R(\underline{x}, y) \land S(\underline{y}, x))$
  $\textsc{Certainty}(\textsc{Circle})$ is in P, but not SQL-rewritable.
- $\textsc{Sink}()$: $\exists x, y, z(R(\underline{x}, z) \land S(\underline{y}, z))$
  $\textsc{Certainty}(\textsc{Sink})$ is in coNP-complete.

The Trichotomy for CERTAINTY($q, \mathcal{I}, \Sigma$)

Theorem (Koutris and Wijsen - 2015, 2017)

If Σ is a set of key constraints with one key per relation and q is a Boolean self-join-free conjunctive query, then one of the following holds.

- CERTAINTY(q, Σ) is SQL-rewritable.
- CERTAINTY(q, Σ) is in P, but not SQL-rewritable.
- CERTAINTY(q, Σ) is coNP-complete.

Moreover, this trichotomy is decidable in quadratic time.

More on the Koutris-Wijsen Trichotomy

- SQL-rewritable: For a query q, there is another query q' such that $q'(\mathcal{I}) = \textsc{Cons}(q, \mathcal{I}, \Sigma)$. For example,

  S: E (id, name, city)

  q = SELECT *E1.name* FROM *E* AS *E1* WHERE *E1.city* = *'London'*;

  q′ = SELECT *E1.name* FROM *E* AS *E1* WHERE *E1.city='London'*
  AND NOT EXISTS (SELECT * FROM *E* AS *E2* WHERE *E2.id* = *E1.id*
  AND *E2.city* != *'London'*);

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  AND NOT EXISTS (SELECT * FROM *E* AS *E2* WHERE *E2.id* = *E1.id*
  AND *E2.city* != *'London'*);

- In P, but not SQL-rewritable: $\textsc{Cons}(q, \mathcal{I}, \Sigma)$ can be efficiently computed, but that algorithm cannot be expressed in SQL

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  AND *E2.city* != *'London'*);

- In P, but not SQL-rewritable: $\textsc{Cons}(q, \mathcal{I}, \Sigma)$ can be efficiently computed, but that algorithm cannot be expressed in SQL

- CoNP-complete: No efficient algorithm can compute $\textsc{Cons}(q, \mathcal{I}, \Sigma)$, unless P = NP.

Satisfiability (SAT)

Definition

Boolean Formula is an expression built from variables, constants, and the Boolean operators conjunction ($\wedge$), disjunction ($\vee$), and negation ($\neg$).

Definition

Boolean SAT Problem: Given a Boolean formula, is it satisfiable?

Example

$\phi = (a \vee b \vee c) \wedge (\neg d) \wedge (b \vee \neg c \vee d) \wedge (\neg a \vee c) \wedge (d \vee e \vee \neg f) \wedge (f)$
Satisfying assignment: $(a, b, c, d, e, f) = (0, 1, 1, 0, 1, 1)$

- Boolean SAT is the most fundamental and most extensively studied NP-complete problem.

Modern SAT Solvers

- SAT Revolution (Biere, Heule, van Maaren, Walsh - 2009):
  "From 100 variables and 200 clauses (in early 1990s) to 1,000,000+ variables and 5,000,000+ clauses in 20 years"
- Advanced algorithms like conflict-driven clause learning and look-ahead techniques, pre-processing and in-processing optimizations
- Widely used as general purpose problem-solving tools
- Mostly open-source, e.g., Lingeling, Glucose, MaxHS

Motivation...

...To build a CQA System

- Research on CQA has not penetrated the industry yet
- Industry relies on ad-hoc data cleaning techniques
- Partly because no comprehensive CQA system exists

...To use SAT Solvers

- Current logic-based approaches to CQA have limitations in terms of the size of the database
- Recent advancements in SAT solving technology
- Natural reductions from the complement of CQA to variants of SAT for broad classes of queries and integrity constraints

Applications of Repairs and CQA

Data Exchange (ten Cate, Halpert, Kolaitis - 2016)

- Conflicting information in the source instance is undesirable for query answering
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Description Logic (Bienvenu and Bourgaux - 2017)

- Various semantics to inconsistency-tolerant query answering in context to ontology-based data access
- Query answering systems such as CQAPri for querying inconsistent knowledge bases

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Fairness in ML (Salimi, Rodriguez, Howe, Suciu - 2019)

- Underlying training data often reflects discrimination
- Notion of repairing the training data for fairness guarantees

Comprehensive CQA System using SAT Solvers

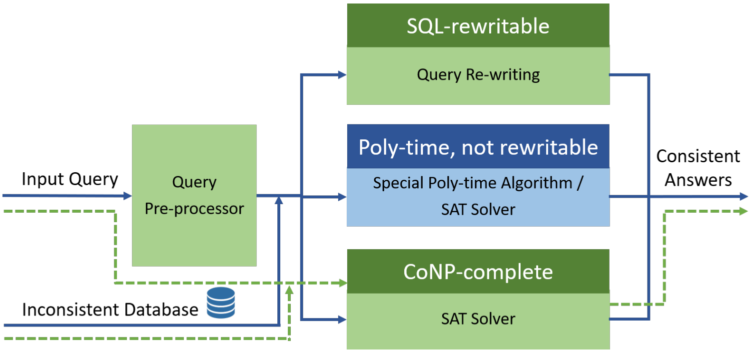

Figure: Envisioned architecture of a modular CQA system

Complement of CERTAINTY(q) to SAT

1. Let g_j be a set of tuples of I that share a key j. For all tuples $f_i \in g_j$, construct a clause u_j such that

$$u_j = \bigvee_{f_i \in g_j} x_{f_i}$$

2. For each minimal witness w_k to q on I, construct a clause v_k such that

$$v_k = \bigvee_{f_i \in w_k} \neg x_{f_i}$$

3. Construct a conjunctive Boolean formula

$$\phi = (u_1 \wedge u_2 \wedge ... \wedge u_m) \wedge (v_1 \wedge v_2 \wedge ... \wedge v_n)$$

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$$\phi = (u_1 \wedge u_2 \wedge ... \wedge u_m) \wedge (v_1 \wedge v_2 \wedge ... \wedge v_n)$$

Fact: ϕ is satisfiable if and only if q is false on some repair of I.

A Short Demo of CAvSAT

Beyond sjfBCQ and Primary Key Constraints

- Primary keys are an important but limited class of integrity constraints

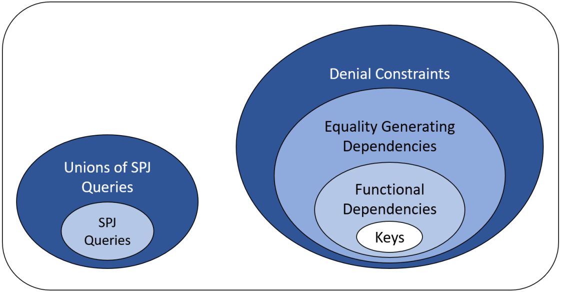

Figure: Classes of integrity constraints and database queries

- Preceding reduction extends naturally for UCQs over databases having arbitrary denial constraints

Experimental Setup

Phase I:

- Synthetically generated databases (1M tuples/relation)
- One key constraint per relation
- Varying inconsistency (5% to 15%)
- 21 conjunctive queries from the literature

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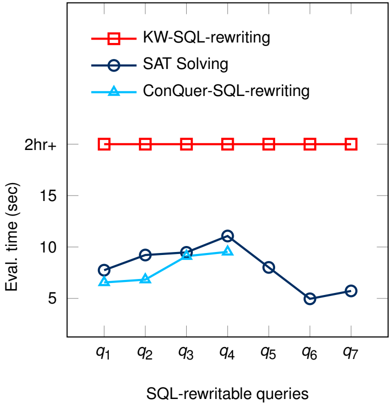
Phase II:

- Real-world data about food and safety inspections of restaurants in Chicago and New York (up to 230K tuples/relation)
- Arbitrary key and functional dependency constraints
- Up to 25% inconsistency
- Five conjunctive queries, one union of conjunctive queries

Experimental Results (Phase I)

- KW-SQL-rewriting: The state-of-the-art generic algorithm for SQL-rewriting (Koutris, Wijsen – 2017)
- ConQuer-SQL-rewriting: A special algorithm suitable for a subclass C_{forest} of SQL-rewritable queries (Fuxman, Fazli, Miller – 2005)



On the Practicality of KW-SQL-rewriting

Schema

```
R1(A,B,C), R3(A,B), R4(A,B,C)
```

Query

```
SELECT R1.C FROM R1, R3, R4
WHERE R1.B=R3.A AND R3.B=R4.A
```

KW-SQL-Rewriting

```
SELECT DISTINCT free_R1.C FROM R1 AS free_R1
WHERE EXISTS(
    SELECT * FROM R1 AS s1
    WHERE NOT EXISTS(
        SELECT * FROM R1 AS r1
        WHERE NOT EXISTS(
            SELECT * FROM R3 AS s2
            WHERE NOT EXISTS(
                SELECT * FROM R3 AS r2
                WHERE NOT EXISTS(
                    SELECT * FROM R4 AS s3
                    WHERE NOT EXISTS(
                        SELECT * FROM R4 AS r3
                        WHERE ((( (s1.A=r1.A)
                        AND (s2.A=r2.A)) AND (s3.A=r3.A))
                        AND (((r2.B!=r3.A) OR (r1.B!=r2.A))
                        OR (r1.C!=free_R1.C)))
                    )
                )
            )
        )
    )
)
```

Experimental Results (Phase I)

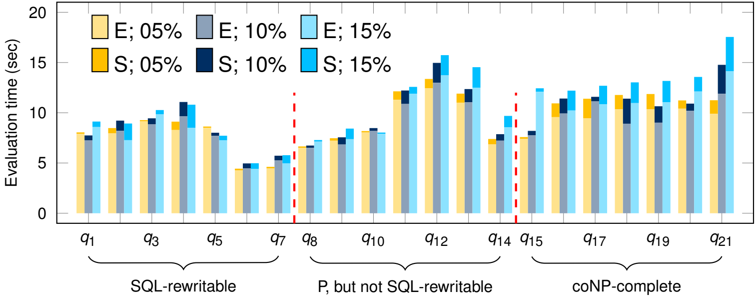
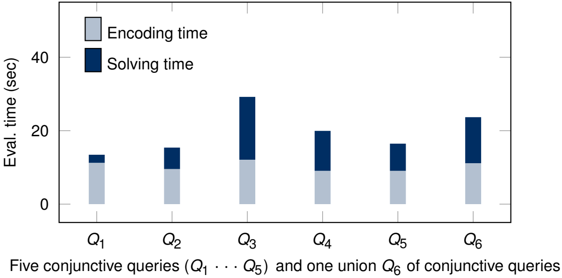


Figure: Time to compute consistent answers using MaxHS v3.0

Experimental Results (Phase II)



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Synopsis and Outlook

Summary

- The framework of repairs provides a scientific approach to cope with inconsistent databases
- While much progress has been made in theory, no comprehensive CQA system exists in practice
- Given the advancements in SAT solving, CAvSAT seems to be a promising approach

Future work

- Investigate the gap between theory and practice w.r.t. CQA
- Conjunctive queries with aggregate functions
- Performance comparison of CAvSAT with existing reduction-based CQA systems

Conjunctive Queries Used On Synthetic Data

FO-rewritable:

$q_1(z) : R_1(\underline{x}, y, z), R_2(\underline{y}, v, w)$

$q_2(z, w) : R_1(\underline{x}, y, z), R_2(\underline{y}, v, w)$

$q_3(z) : R_1(\underline{x}, y, z), R_3(\underline{y}, v), R_2(\underline{v}, u, d)$

$q_4(z, d) : R_1(\underline{x}, y, z), R_3(\underline{y}, v), R_2(\underline{v}, u, d)$

$q_5(z) : R_1(\underline{x}, y, z), R_4(\underline{y, v}, w)$

$q_6(z) : R_1(\underline{x}, y, z), R_2(\underline{x'}, y, w), R_5(\underline{x}, y, d)$

$q_7(z) : R_1(\underline{x}, y, z), R_2(\underline{y}, x, w), R_5(\underline{x}, y, d)$

In P, but not FO-rewritable:

$q_8(z, w) : R_1(\underline{x}, y, z), R_2(\underline{y}, x, w)$

$q_9(z) : R_1(\underline{x}, y, z), R_2(\underline{y}, x, w), R_4(\underline{y}, u, d)$

$q_{10}(z, w, d) : R_1(\underline{x}, y, z), R_2(\underline{y}, x, w), R_4(\underline{y}, u, d)$

$q_{11}(z) : R_1(\underline{x}, y, z), R_2(\underline{y}, x, w)$

$q_{12}(v, d) : R_3(\underline{x}, y), R_6(\underline{y}, z), R_1(\underline{z}, x, d), R_4(\underline{x, u}, v)$

$q_{13}(v) : R_3(\underline{x}, y), R_6(\underline{y}, z), R_7(\underline{z}, x), R_4(\underline{x, u}, v)$

$q_{14}(d) : R_3(\underline{x}, y), R_6(\underline{y}, z), R_1(\underline{z}, x, d), R_7(\underline{x}, u)$

CoNP-complete:

$q_{15}(z) : R_1(\underline{x}, y, z), R_2(\underline{x'}, y, w)$

$q_{16}(z, w) : R_1(\underline{x}, y, z), R_2(\underline{x'}, y, w)$

$q_{17}(z) : R_1(\underline{x}, y, z), R_2(\underline{x'}, y, w), R_4(\underline{y}, u, d)$

$q_{18}(z, w) : R_1(\underline{x}, y, z), R_2(\underline{x'}, y, w), R_4(\underline{y}, u, d)$

$q_{19}(z, w, d) : R_1(\underline{x}, y, z), R_2(\underline{x'}, y, w), R_4(\underline{y}, u, d)$

$q_{20}(z) : R_1(\underline{x}, y, z), R_2(\underline{x'}, y, w), R_4(\underline{y}, u, d), R_3(\underline{u}, v)$

$q_{21}(z, w) : R_1(\underline{x}, y, z), R_2(\underline{x'}, y, w), R_4(\underline{y}, u, d), R_3(\underline{u}, v)$

Queries Used On Real-world Data

$$
\begin{aligned}
Q_1() :& \text{NY\_Restaurants}(x, y, z, w, v) \wedge \text{CH\_Restaurants}(x, y', z', w', v') \\
Q_2(x) :& \text{NY\_Restaurants}(x, y, z, w, v) \wedge \text{CH\_Restaurants}(x, y', z', w', v') \\
Q_3(x) :& \text{NY\_Restaurants}(x, y, z, w, v) \wedge \text{CH\_Restaurants}(x, y', z', w', v') \\
& \wedge \text{NY\_Insp}(y, q, r, s, t) \wedge \text{CH\_Insp}(y', q', r, s', t') \\
Q_4(x, y) :& \text{CH\_Restaurants}(x, y, z, w, v) \wedge \text{CH\_Insp}(y, q, r, s, \text{`Pass'}) \\
Q_5(x, v) :& \text{CH\_Restaurants}(x, y, z, w, v) \wedge \text{NY\_Restaurants}(x, y', z', w', v') \\
& \wedge \text{NY\_Insp}(y', \text{`Not Critical'}, q, r, s) \\
Q_6(x) :& \text{CH\_Restaurants}(x, y, z, w, v) \wedge \text{CH\_Insp}(y, q, r, s, \text{`Fail'}) \\
& \cup \text{NY\_Restaurants}(x, y, z, w, v) \wedge \text{NY\_Insp}(y, q, r, s, \text{`Fail'})
\end{aligned}
$$

The Notion of Possible Answers

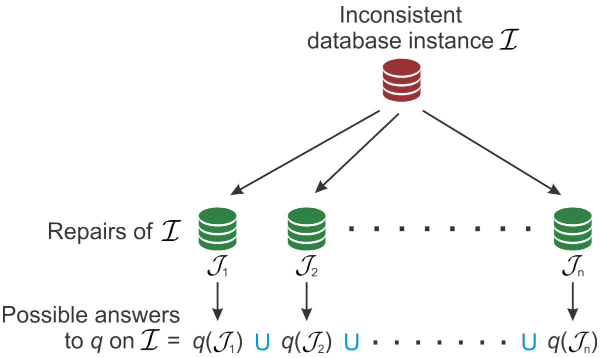

Figure: Possible answers to q on $\mathcal{I}$

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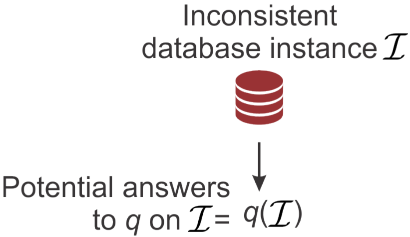

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