Consistent Query Answering

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October 2017

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Database instance D:

- a finite first-order structure
- the information about the world

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- first-order logic formulas
- the properties of the world

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Formula satisfaction in a first-order structure.

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Inconsistent database: $D \not\models IC$

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Whence Inconsistency?

Sources of inconsistency:

- integration of independent data sources with overlapping data
- time lag of updates (eventual consistency)
- unenforced integrity constraints

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- ignoring inconsistency
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▸ CQA

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Dropping conflicting tuples

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FROM Employee
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$\longrightarrow$

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Query results not reliable.

Traditional view

- query results defined irrespective of integrity constraints
- query evaluation may be optimized in the presence of integrity constraints (semantic query optimization)

The Impact of Inconsistency on Queries

Traditional view

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- query evaluation may be optimized in the presence of integrity constraints (semantic query optimization)

Our view

- inconsistency leads to uncertainty
- query results may depend on integrity constraint satisfaction
- inconsistency may be eliminated (repairing) or tolerated (consistent query answering)

Database Repairs

Restoring consistency

- insertion, deletion
- minimal change

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Consistent query answer

- query answer obtained in every repair
- database not changed

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Research Goals

Formal definition

What constitutes reliable (consistent) information in an inconsistent database.

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Algorithms

How to compute consistent information.

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Computational complexity analysis

- tractable vs. intractable classes of queries and integrity constraints
- tradeoffs: complexity vs. expressiveness.

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- preferably using DBMS technology.

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Implementation

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Applications

- data cleaning

Repair D' of a database D w.r.t. the integrity constraints IC:

- D': over the same schema as D
- $D' \models IC$
- symmetric difference between D and D' is minimal.

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Basic Notions

Repair D' of a database D w.r.t. the integrity constraints IC:

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Another incarnation of the idea of sure/certain query answers (Lipski [Jr.79]).

A Logical Aside

Logical inconsistency

- inconsistent database: database facts together with integrity constraints form an inconsistent set of formulas
- trivialization of reasoning does not occur because constraints are not used in relational query evaluation.

Exponentially many repairs

Example relation $R(A, B)$

- violates the dependency $A \rightarrow B$
- has 2^n repairs.

A	B
a_1	b_1
a_1	c_1
a_2	b_2
a_2	c_2
...	
a_n	b_n
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$A \rightarrow B$

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It is impractical to apply the definition of CQA directly.

Query Rewriting

Given a query Q and a set of integrity constraints IC, build a query Q^{IC} such that for every database instance D

> *the set of answers to Q^{IC} in D = the set of consistent answers to Q in D w.r.t. IC.*

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Representing all repairs

Given IC and D:

1. build a space-efficient representation of all repairs of D w.r.t. IC
2. use this representation to answer (many) queries.

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Logic programs

Given IC, D and Q:

1. build a logic program $P_{IC,D}$ whose models are the repairs of D w.r.t. IC
2. build a logic program P_Q expressing Q
3. use a logic programming system that computes the query atoms present in all models of $P_{IC,D} \cup P_Q$.

Constraint classes

Universal constraints

$\forall.\ A_1 \wedge \cdots \wedge A_n \Rightarrow B_1 \vee \cdots \vee B_m$

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Example

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Building queries that compute CQAs

- relational calculus (algebra) $\rightsquigarrow$ relational calculus (algebra)
- SQL $\rightsquigarrow$ SQL
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$Emp(x, y, z)$

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Integrity constraint

$\forall\ x, y, z, y', z'.\ \neg Emp(x, y, z) \vee \neg Emp(x, y', z') \vee z = z'$

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- leads to PTIME data complexity

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$\forall\ x, y, z, y', z'.\ \neg Emp(x, y, z) \lor \neg Emp(x, y', z') \lor z = z'$

Rewritten query

$Emp(x, y, z) \land \forall\ y', z'.\ \neg Emp(x, y', z') \lor z = z'$

The Scope of Query Rewriting

(Arenas, Bertossi, Ch. [ABC99])

- Integrity constraints: binary universal
- Queries: conjunctions of literals (relational algebra: $\sigma, \times, -$)

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(Fuxman, Miller [FM07])

- Integrity constraints: primary key functional dependencies
- Queries: C_{forest}
  - a class of conjunctive queries ($\pi, \sigma, \times$)
  - no cycles
  - no non-key or non-full joins
  - no repeated relation symbols
  - no built-ins

SQL Rewriting

SQL query

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SELECT Name FROM Emp
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       (SELECT * FROM EMPLOYEE e2
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(Fuxman, Fazli, Miller [FM05])

- ConQuer: a system for computing CQAs
- conjunctive (C_{forest}) and aggregation SQL queries
- databases can be annotated with consistency indicators
- tested on TPC-H queries and medium-size databases

Conflict Hypergraph

Vertices

Tuples in the database.

(Gates, Redmond, 20M)

(Musk, Palo Alto, 10M)

(Gates, Redmond, 30M)

Conflict Hypergraph

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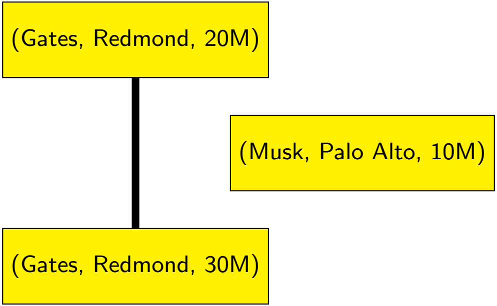
Tuples in the database.

Edges

Minimal sets of tuples violating a constraint.



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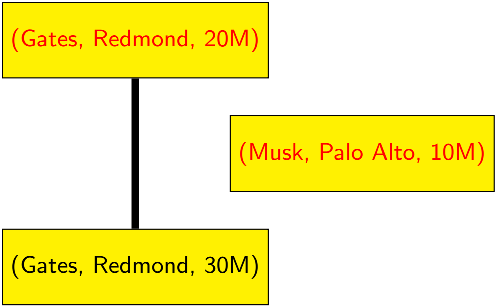
Maximal independent sets in the conflict graph.



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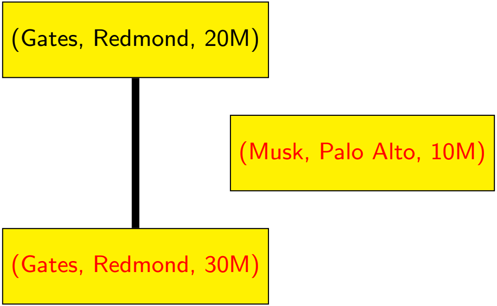

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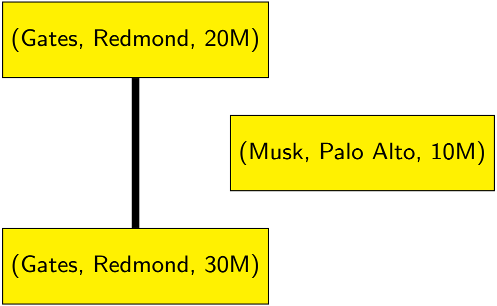

Representation applicable only to denial constraints.

Algorithm HProver

INPUT: query Φ a disjunction of ground literals, conflict hypergraph G
OUTPUT: is Φ false in some repair of D w.r.t. IC?
ALGORITHM:

1. $\neg\Phi = P_1(t_1) \wedge \cdots \wedge P_m(t_m) \wedge \neg P_{m+1}(t_{m+1}) \wedge \cdots \wedge \neg P_n(t_n)$
2. find a consistent set of facts S such that
   - $S \supseteq \{P_1(t_1), \ldots, P_m(t_m)\}$
   - for every fact $A \in \{P_{m+1}(t_{m+1}), \ldots, P_n(t_n)\}$: $A \notin D$ or there is an edge $E = \{A, B_1, \ldots, B_m\}$ in G and $S \supseteq \{B_1, \ldots, B_m\}$.

Computing CQAs Using Conflict Hypergraphs

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(Ch., Marcinkowski, Staworko [CMS04])

- Hippo: a system for computing CQAs in PTIME
- quantifier-free queries and denial constraints
- only edges of the conflict hypergraph are kept in main memory
- optimization can eliminate many (sometimes all) database accesses in HProver
- tested for medium-size synthetic databases

Specifying repairs as answer sets of logic programs

- (Arenas, Bertossi, Ch. [ABC03])
- (Greco, Greco, Zumpano [GGZ03])
- (Calì, Lembo, Rosati [CLR03b])

Specifying repairs as answer sets of logic programs

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Example

$emp(x, y, z) \leftarrow emp_D(x, y, z), not\ dubious\_emp(x, y, z).$
$dubious\_emp(x, y, z) \leftarrow emp_D(x, y, z), emp(x, y', z'), y \neq y'.$
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Answer sets

- $\{emp(Gates, Redmond, 20M), emp(Musk, PaloAlto, 10M), \ldots\}$
- $\{emp(Gates, Redmond, 30M), emp(Musk, PaloAlto, 10M), \ldots\}$

Logic Programs for computing CQAs

Logic Programs

- disjunction and classical negation
- checking whether an atom is in all answer sets is Π_2^p-complete
- `dlv`, `smodels`, ...

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- combines CQA with data integration (GAV)
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complexity

Co-NP-completeness of CQA

Theorem (Ch., Marcinkowski [CM05a])

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Proof.

Membership: V is a repair iff $V \models IC$ and $W \not\models IC$ if $W = V \cup M$.
Co-NP-hardness: reduction from MONOTONE 3-SAT.

1. Positive clauses $\beta_1 = \phi_1 \wedge \cdots \wedge \phi_m$, negative clauses $\beta_2 = \psi_{m+1} \wedge \cdots \wedge \psi_l$.
2. Database D contains two binary relations $R(A, B)$ and $S(A, B)$:
    - $R(i, p)$ if variable p occurs in ϕ_i, $i = 1, \ldots, m$.
    - $S(i, p)$ if variable p occurs in ψ_i, $i = m + 1, \ldots, l$.
3. A is the primary key of both R and S.
4. Query $Q \equiv \exists x, y, z. \left(R(x, y) \wedge S(z, y)\right)$.
5. There is an assignment which satisfies $\beta_1 \wedge \beta_2$ iff there exists a repair in which Q is false.

□

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Q does not belong to C_{forest}.

Data complexity of CQA

	Primary keys	*Arbitrary keys*	*Denial*	*Universal*
$\sigma, \times, -$				
$\sigma, \times, -, \cup$				
σ, π				
$\sigma, \pi, \times$				
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Data complexity of CQA

	Primary keys	*Arbitrary keys*	*Denial*	*Universal*
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- (Arenas, Bertossi, Ch. [ABC99])

Data complexity of CQA

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$\sigma, \times, -, \cup$	PTIME	PTIME	PTIME	
σ, π	PTIME	co-NPC	co-NPC	
$\sigma, \pi, \times$	co-NPC	co-NPC	co-NPC	
$\sigma, \pi, \times, -, \cup$	co-NPC	co-NPC	co-NPC	

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- (Fuxman, Miller [FM07])

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- (Arenas, Bertossi, Ch. [ABC99])
- (Ch., Marcinkowski [CM05a])
- (Fuxman, Miller [FM07])
- (Staworko, Ph.D., 2007), (Staworko, Ch., 2008):
  - quantifier-free queries
  - co-NPC for full TGDs and denial constraints
  - PTIME for acyclic full TGDs, join dependencies and denial constraints

Last

Dichotomy

Complexity of self-join-free conjunctive queries (Koutris, Wijsen [KW17])

- it can be decided whether or not CQA can be computed by a first-order query (and if so the corresponding SQL query is easily computable)
- computing CQA is either in PTIME or co-NP complete (and it can be decided which case applies)

The Explosion of Semantics

Tuple-based repairs

- asymmetric treatment of insertion and deletion:
  - repairs by minimal deletions only (Ch., Marcinkowski [CM05a]): data possibly incorrect but complete
  - repairs by minimal deletions and arbitrary insertions (Calì, Lembo, Rosati [CLR03a]): data possibly incorrect and incomplete
- minimal cardinality changes (Lopatenko, Bertossi [LB07]), more...

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Attribute-based repairs

- repairs of minimum cost (Bohannon et al. [BFFR05])
- checking existence of a repair of cost $< K$ NP-complete.

▸ Clean ▸ Last

The Need for Attribute-based Repairing

Tuple-based repairing leads to information loss.

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EmpDept

Name	*Dept*	*Location*
John	Sales	Buffalo
Mary	Sales	Toronto

Name $\rightarrow$ Dept

Dept $\rightarrow$ City

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Repair the lossless join decomposition:

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Attribute-based Repairs through Tuple-based Repairs (Wijsen [Wij06])

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Probabilistic framework for “dirty” databases

(Andritsos, Fuxman, Miller [AFM06])

- potential duplicates identified and grouped into clusters
- worlds $\approx$ repairs: one tuple from each cluster
- world probability: product of tuple probabilities
- clean answers: in the query result in some (supporting) world
- clean answer probability: sum of the probabilities of supporting worlds
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Salaries with probabilities

EmpProb

Name	*Salary*	Prob
Gates	20M	0.7
Gates	30M	0.3
Musk	10M	0.5
Musk	20M	0.5

SQL query

```
SELECT Name
FROM EmpProb e
WHERE e.Salary > 15M
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Computing Clean Answers

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SQL rewritten query

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Name	Prob
Gates	1
Musk	0.5

Good News

Technology

- practical methods for CQA for subsets of SQL:
  - restricted conjunctive/aggregation queries, primary/foreign-key constraints
  - quantifier-free queries, denial constraints/acyclic TGDs/JDs
  - LP-based approaches for expressive query/constraint languages
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The CQA Community

- over 30 active researchers
- [ABC99] has over 800 citations
- 10-15 doctoral dissertations in Europe and North America
- 2007 SIGMOD Doctoral Dissertation Award (Ariel Fuxman)
- overview papers [BC03, Ber06, Cho07, CM05b]

Taking stock

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Topics of recent interest

- CQA under prioritized repairs
- CQA and knowledgebases
- CQA and temporal databases
- repairing: algorithms, heuristics
- repairing the database and the schema
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Acknowledgments

Marcelo Arenas
Alessandro Artale
Leo Bertossi
Loreto Bravo
Andrea Calì
Àlvaro Cortés
Thomas Eiter
Wenfei Fan
Enrico Franconi
Ariel Fuxman
Gianluigi Greco
Sergio Greco
Claudio Gutierrez
Roger He
Phokion Kolaitis
Domenico Lembo
Maurizio Lenzerini
Jerzy Marcinkowski
Renée Miller
Cristian Molinaro
Vijay Raghavan
Riccardo Rosati
Gunter Saake
Jeremy Spinrad
Sławek Staworko
David Toman
Jef Wijsen

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