Consistent Query Answering: Five Easy Pieces

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When was Alberto Mendelzon born?

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> *Inconsistencies cannot both be* right; *but, imputed to man, they may both be* true.
>
> Samuel Johnson

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Database instance D:

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

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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
- dataspace systems,...

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Eliminating inconsistency?

- not enough information, time, or money
- difficult, impossible or undesirable
- unnecessary: queries may be insensitive to inconsistency

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Query results not reliable.

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FROM Employee
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$\longrightarrow$

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Gates
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Horizontal Decomposition

Decomposition into two relations:

- violators
- the rest

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Exceptions to Constraints

Weakening the contraints:

- functional dependencies $\longrightarrow$ denial constraints

[Borgida: TODS'85]

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except Name='Gates'

The Impact of Inconsistency on Queries

Traditional view

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

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"Post-modernist" view

- inconsistency reflects uncertainty
- query results may depend on integrity constraint satisfaction
- inconsistency may be eliminated or tolerated

Database Repairing

Restoring consistency:

- insertion, deletion, update
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Consistent query answer:

Query answer obtained in every repair.

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Formal definition

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

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

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Applications

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

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Another incarnation of the idea of sure query answers [Lipski: TODS'79].

A Logical Aside

Belief revision

- semantically: repairing $\equiv$ revising the database with integrity constraints
- consistent query answers $\equiv$ counterfactual inference.

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
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...	
a_n	b_n
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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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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

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Functional dependencies

$X \rightarrow Y$:

- a key dependency in F if X is a key
- a primary-key dependency: only one key exists

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$R[X] \subseteq S[Y]$:

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Example foreign key constraint

$M[Manager] \subseteq M[Name]$

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Building queries that compute CQAs

- relational calculus (algebra) $\rightsquigarrow$ relational calculus (algebra)
- SQL $\rightsquigarrow$ SQL
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$\forall\ x, y, z, y', z'.\ \neg Emp(x, y, z) \vee \neg Emp(x, y', z') \vee z = z'$

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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.: PODS'99]

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

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[Fuxman, Miller: ICDT'05]

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

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SELECT Name FROM Emp
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[Fuxman, Fazli, Miller: SIGMOD'05]

- 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)

(Grove, Santa Clara, 10M)

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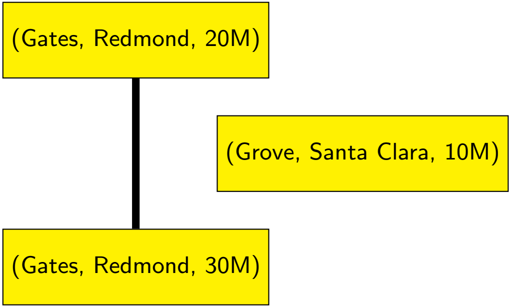
Edges

Minimal sets of tuples violating a constraint.



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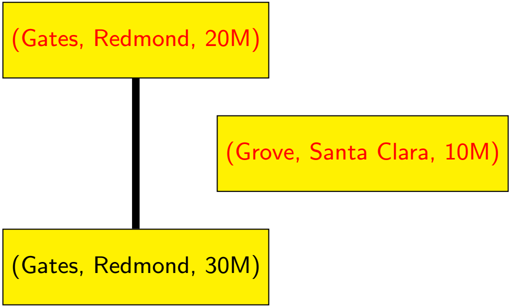

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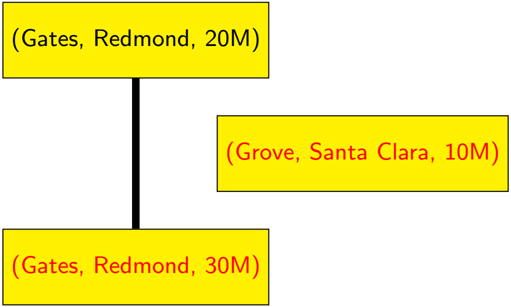

Algorithm HProver

INPUT: query Φ a disjunction of ground atoms, 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: CIKM'04]

- 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

Logic programs

Specifying repairs as answer sets of logic programs

- [Arenas, Bertossi, Ch.: FQAS'00, TPLP'03]
- [Greco, Greco, Zumpano: LPAR'00, TKDE'03]
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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

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

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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- universal constraints
- approach unlikely to yield tractable cases

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INFOMIX [Eiter et al.: ICLP'03]

- combines CQA with data integration (GAV)
- uses `dlv` for repair computations
- optimization techniques: localization, factorization
- tested on small-to-medium-size legacy databases

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Theorem (Ch., Marcinkowski: Inf. Comp.'05)

For primary-key functional dependencies and conjunctive queries, consistent query answering is data-complete for co-NP.

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Proof.

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

1. Positive clauses $\beta_1 = \phi_1 \wedge \ldots \phi_m$, negative clauses $\beta_2 = \psi_{m+1} \ldots \wedge \psi_l$.
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 $Q \equiv \exists x, y, z.\ \big(R(x,y) \wedge S(z,y)\big)$.
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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Membership: S is a repair iff $S \models IC$ and $W \not\models IC$ if $W = S \cup A$.
Co-NP-hardness: reduction from MONOTONE 3-SAT.

1. Positive clauses $\beta_1 = \phi_1 \wedge \ldots \phi_m$, negative clauses $\beta_2 = \psi_{m+1} \ldots \wedge \psi_l$.
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 $Q \equiv \exists x, y, z. \; \big(R(x, y) \wedge S(z, y)\big)$.
5. There is an assignment which satisfies $\beta_1 \wedge \beta_2$ iff there exists a repair in which Q is false.

□

Q does not belong to C_{forest}.

Data complexity of CQA

	Primary keys	*Arbitrary keys*	*Denial*	*Universal*
$\sigma, \times, -$				
$\sigma, \times, -, \cup$				
σ, π				
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- [Fuxman, Miller: ICDT'05]
- [Staworko, Ch.: unpublished]

The Semantic Explosion

Tuple-based repairs

- asymmetric treatment of insertion and deletion:
  - repairs by minimal deletions only [Ch., Marcinkowski: Inf.Comp.'05]: data possibly incorrect but complete
  - repairs by minimal deletions and arbitrary insertions [Calì, Lembo, Rosati: PODS'03]: data possibly incorrect and incomplete
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- (A) ground and non-ground repairs [Wijsen: TODS'05]
- (B) project-join repairs [Wijsen: FQAS'06]
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Computational complexity

- (A) and (B): similar to tuple based repairs
- (C) and (D): checking existence of a repair of cost $< K$ NP-complete.

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Tuple-based repairing leads to information loss.

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John	Sales	Buffalo
Mary	Sales	Toronto

Name $\longrightarrow$ Dept

Dept $\longrightarrow$ City

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Attribute-based Repairs through Tuple-based Repairs

Repair a lossless join decomposition.

The decomposition:

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Probabilistic framework for “dirty” databases

[Andritsos, Fuxman, Miller: ICDE’06]

- 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
Grove	10M	0.5
Grove	20M	0.5

Name → Salary

Computing Clean Answers

SQL query

```
SELECT Name
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WHERE e.Salary > 15M
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Name	Prob
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Grove	0.5

Consistent Query Answering: Looking Back

PODS'99, June 1999

- Arenas, Bertossi, Ch.: "Consistent Query Answers in Inconsistent Databases."

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Other concurrent events:

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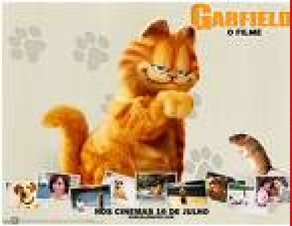

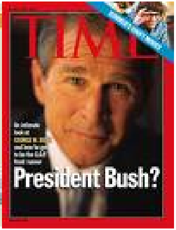

Taking Stock: Good News

Technology

- practical methods for CQA for a subset of SQL:
  - restricted conjunctive/aggregation queries, primary/foreign-key constraints
  - quantifier-free queries/denial constraints
  - LP-based approaches for expressive query/constraint languages
- implemented in prototype systems
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The CQA Community

- over 30 active researchers
- up to 100 publications (since 1999)
- outreach to the AI community (qualified success)

Taking Stock: Initial Progress

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"Blending in" CQA

- data integration: tension between repairing and satisfying source-to-target dependencies
- peer-to-peer: how to isolate an inconsistent peer?

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Extensions

- nulls:
  - repairs with nulls?
  - clean semantics vs. SQL conformance
- priorities:
  - preferred repairs
  - application: conflict resolution
- XML
  - notions of integrity constraint and repair
  - repair minimality based on tree edit distance?

Taking Stock: Largely Open Issues

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Applications

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- repairing vs. CQA: data and query characteristics
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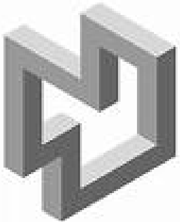
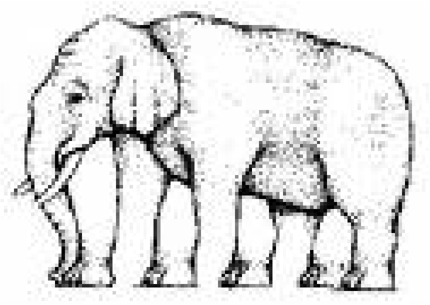


Inconsistent elephant (by Oscar Reutersvärd)



Selected overview papers

L. Bertossi, J. Chomicki, Query Answering in Inconsistent Databases. In *Logics for Emerging Applications of Databases,* J. Chomicki, R. van der Meyden, G. Saake [eds.], Springer-Verlag, 2003.

J. Chomicki and J. Marcinkowski, On the Computational Complexity of Minimal-Change Integrity Maintenance in Relational Databases. In *Inconsistency Tolerance,* L. Bertossi, A. Hunter, T. Schaub, editors, Springer-Verlag, 2004.

L. Bertossi, Consistent Query Answering in Databases. SIGMOD Record, June 2006.

"Five Easy Pieces"

Bobby: I'd like a plain omelet. No potatoes, tomatoes instead. A cup of coffee and wheat toast.
Waitress: No substitutions.
Bobby: What do you mean? You don't have any tomatoes?
Waitress: Only what's on the menu. You can have a number two - a plain omelet. It comes with cottage, fries, and rolls.
Bobby: Yea, I know what it comes with, but it's not what I want.
Waitress: I'll come back when you make up your mind.
Bobby: Wait a minute, I have made up my mind. I'd like a plain omelet, no potatoes on the plate. A cup of coffee and a side order of wheat toast.
Waitress: I'm sorry, we don't have any side orders of toast. I'll give you a English muffin or a coffee roll.
Bobby: What do you mean "you don't make side orders of toast"? You make sandwiches, don't you?
Waitress: Would you like to talk to the manager?
Bobby: You've got bread. And a toaster of some kind?
Waitress: I don't make the rules.
Bobby: OK, I'll make it as easy for you as I can. I'd like an omelet, plain, and a chicken salad sandwich on wheat toast, no mayonnaise, no butter, no lettuce. And a cup of coffee.
Waitress: A number two, chicken sal san. Hold the butter, the lettuce, the mayonnaise, and a cup of coffee. Anything else?
Bobby: Yeah, now all you have to do is hold the chicken, bring me the toast, give me a check for the chicken salad sandwich, and you haven't broken any rules.
Waitress: You want me to hold the chicken, huh?
Bobby: I want you to hold it between your knees.