Consistent Query Answering: The First Ten Years

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Integrity constraints (dependencies)

Database instance D:

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

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Formula satisfaction in a first-order structure.

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Gates	Redmond	30M
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Name $\rightarrow$ City Salary

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Inconsistent database: $D \not\models \Sigma$

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Sources of inconsistency:

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

▸ CQA

Whence Inconsistency?

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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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Living with inconsistency?

- ignoring inconsistency
- modifying the schema
- exceptions to constraints.

▸ CQA

Ignoring Inconsistency

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Ignoring Inconsistency

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Query results not reliable.

Horizontal Decomposition

Decomposition into two relations:

- violators
- the rest

(De Bra, Paredaens [DBP83])

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Weakening the contraints:

- functional dependencies $\rightsquigarrow$ denial constraints

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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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Our view

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

Restoring consistency:

- insertion, deletion
- minimal change

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Query answer obtained in every repair.

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Name → City Salary

SELECT Name
FROM Employee
WHERE Salary $\geq$ 10M

Name
Gates
Jobs

Formal definition

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

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Algorithms

How to compute consistent information.

Research Goals

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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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Applications

???

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

- D': over the same schema as D
- $D' \models IC$
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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 $A \longrightarrow B$
- 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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$A \longrightarrow B$

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

$\forall.\ \neg A_1 \vee \cdots \vee \neg A_n \vee B_1 \vee \cdots \vee B_m$

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$\forall.\ \neg M(n, s, m) \vee \neg M(m, t, w) \vee s \leq t$

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$X \rightarrow Y$:

- a key dependency in F if $Y = U$
- a primary-key dependency: only one key exists

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Name $\rightarrow$ Address Salary

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Example foreign key constraint

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

Building queries that compute CQAs

- relational calculus (algebra) $\leadsto$ relational calculus (algebra)
- SQL $\leadsto$ SQL
- leads to PTIME data complexity

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Integrity constraint

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

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Rewritten query

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

(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
- Generalization: conjunctive queries expressed as rooted rules (Wijsen [Wij07])

SQL query

```
SELECT Name FROM Emp
WHERE Salary ≥ 10K
```

SQL Rewriting

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SQL rewritten query

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SELECT e1.Name FROM Emp e1
WHERE e1.Salary ≥ 10K AND NOT EXISTS
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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)

(Grove, Santa Clara, 10M)

(Gates, Redmond, 30M)

Conflict Hypergraph

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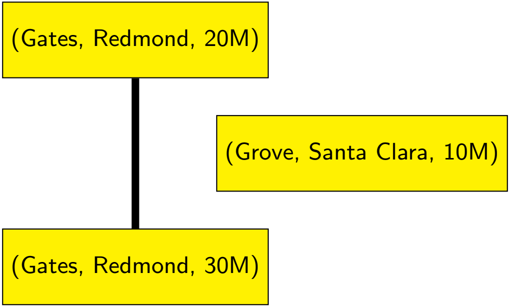
Tuples in the database.

Edges

Minimal sets of tuples violating a constraint.



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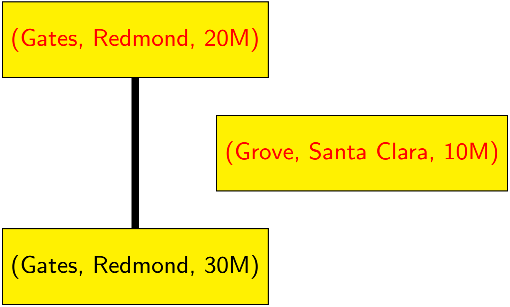
Maximal independent sets in the conflict graph.



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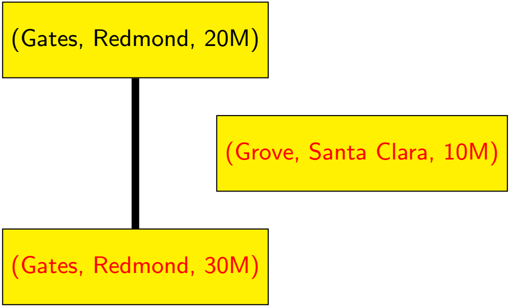

Algorithm HProver

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 $S \supseteq \{B_1, \ldots, B_m\}$.

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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

Logic programs

Specifying repairs as answer sets of logic programs

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

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Example

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

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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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- arbitrary first-order queries
- universal constraints
- approach unlikely to yield tractable cases

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- approach unlikely to yield tractable cases

INFOMIX (Eiter et al. [EFGL03])

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

Inconsistency and Incompleteness

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$$Emp(Gates, Redmond, 20M) \vee Emp(Gates, Redmond, 30M)$$

$$Emp(Jobs, Cupertino, 10M)$$

Minimal models

Minimal models

Repairs vs. minimal models (Molinaro, Ch., Marcinkowski, 2008)

- For denial constraints, the set of repairs of an instance can be represented as the set of minimal models of a disjunctive database of at most exponential size
- The size of the disjunctive database is polynomial for a primary-key FD but may be exponential for two key FDs or one non-key FD.

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Conclusion

It is unlikely that new tractable cases of CQA will be obtained through the disjunctive database representation of the repairs:

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- but (Imielinski, van der Meyden, Vadaparty [IvdMV95])...

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Jobs	Cupertino	10M

Theorem (Ch., Marcinkowski [CM05a])

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

Co-NP-completeness of CQA

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Proof.

Membership: S is a repair iff $S \models IC$ and $W \not\models IC$ if $W = S \cup M$.
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 $Q \equiv \exists x, y, z.\ \big(R(x, y) \wedge S(z, y)\big)$.
5. There is an assignment which satisfies $\beta_1 \wedge \beta_2$ iff there exists a repair in which Q is false.

$\square$

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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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- (Arenas, Bertossi, Ch. [ABC99])

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σ, π	PTIME	co-NPC	co-NPC	
$\sigma, \pi, \times$	co-NPC	co-NPC	co-NPC	
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σ, π	PTIME	co-NPC	co-NPC	Π_2^p-complete
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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

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
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- (A) ground and non-ground repairs (Wijsen [Wij05])
- (B) project-join repairs (Wijsen [Wij06])
- (C) repairs minimizing Euclidean distance (Bertossi et al. [BBFL08])
- (D) repairs of minimum cost (Bohannon et al. [BFFR05])

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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.

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 $\longrightarrow$ Dept

Dept $\longrightarrow$ City

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

Repair the lossless join decomposition:

$$\pi_{Name,Dept}(EmpDept) \bowtie \pi_{Dept,Location}(EmpDept)$$

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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
Jobs	10M	0.5
Jobs	20M	0.5

SQL query

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

SQL query

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SELECT Name
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SQL rewritten query

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Name → Salary

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```

$\longrightarrow$

Name	Prob
Gates	1
Jobs	0.5

Taking Stock: 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
- (slow) emergence of generic techniques
- implemented in prototype systems
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The CQA Community

- over 30 active researchers
- over 100 publications (since 1999)
- at least 8 doctoral dissertations in Europe and North America
- 2007 SIGMOD Doctoral Dissertation Award (Ariel Fuxman)
- overview papers [BC03, Ber06, Cho07, CM05b]

Taking Stock: Initial Progress

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"Blending in" CQA

- data integration: tension between repairing and satisfying source-to-target dependencies

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"Blending in" CQA

- data integration: tension between repairing and satisfying source-to-target dependencies

Extensions

- uncertainty:
  - inconsistency leads to but cannot be reduced to uncertainty
  - repairs vs. possible worlds
  - probabilistic data
  - nulls: SQL conformance
- priorities:
  - preferred repairs
  - application: conflict resolution
- XML
  - notions of integrity constraint and repair
  - repair minimality based on tree edit distance?
- aggregate constraints

Taking Stock: Largely Open Issues

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Applications

- no deployed applications
- repairing vs. CQA: data and query characteristics
- heuristics for CQA and repairing

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CQA in context

- taming the semantic explosion
- CQA and data cleaning
- CQA and schema matching/mapping

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- repair checking
- defining measures of consistency
- proving non-existence of rewritings

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