Consistent Query Answering

Opportunities and Limitations

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Integrity constraints

Integrity constraints describe valid database instances. Examples:

- functional dependencies (FDs): “*every employee has a single salary.*”
- denial constraints: “*no employee can make more than her manager.*”
- inclusion dependencies (INDs): “*managers have to be employees.*”

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An inconsistent database violates the constraints.

Traditional view

Integrity constraints are always enforced.

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Emp

EmpName	*Address*	*Salary*
B. Gates	Redmond, WA	20M
B. Gates	Redmond, WA	30M
A. Grove	Santa Clara, CA	10M

Functional dependency:

$EmpName \rightarrow Address\ Salary$

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Functional dependency:

$EmpName \rightarrow Address\ Salary$

This instance cannot arise but ... consider data integration.

Ignoring inconsistency

```
SELECT *
FROM Emp
WHERE Salary < 25M
```

$\Rightarrow$

B. Gates	Redmond, WA	20M
A. Grove	Santa Clara, CA	10M

Ignoring inconsistency

```
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FROM Emp
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```

⇒

B. Gates	Redmond, WA	20M
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The result is not fully reliable.

Quarantining inconsistency

The facts involved in an inconsistency are not used in the derivation of query answers [Bry, IICIS'97].

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$\Rightarrow$ $\boxed{\text{A. Grove} \quad \text{Santa Clara, CA} \quad \text{10M}}$

But what about

```
SELECT EmpName
FROM Emp
WHERE Salary > 10K
```

$\Rightarrow$ $\boxed{\text{A. Grove}}$

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⇒

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Partial information cannot be obtained.

Constraints with exceptions

Weaken the constraints [Borgida, TODS'85], without affecting query evaluation.

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EmpName	*Address*	*Salary*
B. Gates	Redmond, WA	20M
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A. Grove	Santa Clara, CA	10M

Constraint with exception:

$$(\forall x, y, z, y', z')\neg[Emp(x, y, z) \land Emp(x, y', z') \land y \neq y' \land x \neq \mathsf{B.Gates}]$$

Data cleaning

Emp

EmpName	*Address*	*Salary*
B. Gates	Redmond, WA	20M
B. Gates	Redmond, WA	30M
A. Grove	Santa Clara, CA	10M

Functional dependency:

$EmpName \rightarrow Address\ Salary$

Data cleaning

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EmpName	*Address*	*Salary*
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Functional dependency:

$EmpName \rightarrow Address\ Salary$

Repair:

EmpName	*Address*	*Salary*
B. Gates	Redmond, WA	30M
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EmpName	*Address*	*Salary*
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Functional dependency:

$EmpName \rightarrow Address\ Salary$

Repair:

EmpName	*Address*	*Salary*
B. Gates	Redmond, WA	30M
A. Grove	Santa Clara, CA	10M

Some information is lost.

CQA: a query-driven approach

Consider all repairs: possible databases that result from fixing the original database in a minimal way.

Return all the answers that belong to the result of query evaluation in every repair (consistent answers).

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B. Gates	Redmond, WA	20M
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Repairs:

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FROM Emp
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```

$\Rightarrow$

A. Grove	Santa Clara, CA	10M

But

```
SELECT EmpName
FROM Emp
WHERE Salary > 10K
```

$\Rightarrow$

B. Gates
A. Grove

Inconsistent databases

There are many situations when users want/need to live with inconsistent databases:

- integration of heterogeneous databases with overlapping information
- not enough information to resolve inconsistencies
- preservation of all data (even erroneous)
- the consistency of the database will be restored by executing further transactions
- inconsistency wrt "soft" integrity constraints (those that we hope to see satisfied but do not/cannot check) process

Research goals

Formal definition of reliable ("consistent") information in an inconsistent database.

Computational mechanisms for obtaining consistent information.

Computational complexity analysis:

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

Implementation:

- preferably using DBMS technology.

Plan of the talk

1. repairs and consistent query answers
2. computing consistent query answers to relational algebra/calculus/SQL queries
3. extensions and new directions:
   - other notions of repair
   - probabilistic databases
4. further active research directions
5. related work
6. lessons of CQA research
7. the CQA community

Constraint classes

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

Denial: $\forall.\ \neg A_1 \vee \cdots \vee \neg A_n.$

Functional dependencies (FDs): $X \rightarrow Y.$

Inclusion dependencies (INDs): $P[X] \subseteq R[Y].$

Consistent query answers

Arenas, Bertossi, Ch. [PODS'99].

Repair:

- a database that satisfies the integrity constraints
- difference from the given database is minimal (the set of inserted/deleted facts is minimal under set inclusion).

A tuple $(a_1, \ldots, a_n)$ is a consistent query answer to a query $Q(x_1, \ldots, x_n)$ in a database r if it is an element of the result of Q in every repair of r.

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.

Computational issues

There are too many repairs to evaluate the query in each of them.

A	B
a_1	b_1
a_1	b'_1
a_2	b_2
a_2	b'_2
$\cdots$	
a_n	b_n
a_n	b'_n

Under the functional dependency $A \rightarrow B$, this instance has 2^n repairs.

Computing consistent query answers

Query rewriting: given a query Q and a set of integrity constraints, construct a query Q' such that for every database instance r

> the set of answers to Q' in r = the set of consistent answers to Q in r.

Representing all repairs: given a set of integrity constraints and a database instance r:

1. construct a space-efficient representation of all repairs of r
2. use this representation to answer (many) queries.

Specifying repairs as logic programs.

Query rewriting

First-order queries transformed using semantic query optimization techniques: [Arenas, Bertossi, Ch., PODS'99].

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Functional dependencies:

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

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Query: $Emp(x,y,z)$.

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Query: $Emp(x,y,z)$.

Transformed query:

$$\begin{aligned} Emp(x,y,z) \quad & \wedge \quad (\forall y')(\forall z')(\neg Emp(x,y',z') \vee y = y') \\ & \wedge \quad (\forall y')(\forall z')(\neg Emp(x,y',z') \vee z = z'). \end{aligned}$$

Scope of query rewriting

Query rewriting:

- queries involving conjunctions of literals (*relational algebra*: $\sigma, \times, -$) and binary universal integrity constraints [Arenas, Bertossi, Ch., PODS'99].
- existentially-quantified conjunctions ($\pi, \sigma, \bowtie$) and single-key dependencies [Fuxman, Miller, ICDT'05]:
  - *CTree* queries ($\approx$ no non-key joins)
  - extended to exclusion dependencies [Grieco et al., CIKM'05].

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

$\longmapsto$

```
SELECT Name
FROM Emp e1
WHERE Salary > 10K
  AND NOT EXISTS
      (SELECT *
       FROM EMPLOYEE e2
       WHERE e2.Name = e1.Name
         AND e2.Salary <= 10K)
```

Experimental results (ConQuer)

[Fuxman, Fazli, Miller, SIGMOD'05].

The system ConQuer:

- back-end: DB2 UDB.
- query rewriting into SQL, producing unnested queries
- queries from the TPC-H workload
- databases can be annotated with consistency indicators
- tested for synthetic databases with 400K–8M tuples, 0–50% conflicts
- relatively little overhead compared to evaluating the original query using the backend

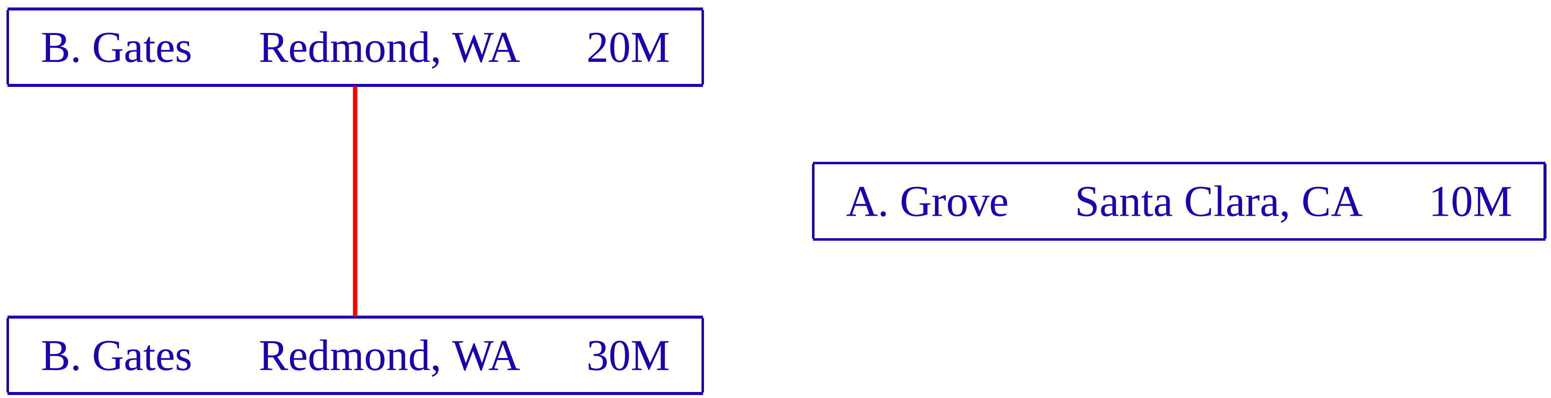
Conflict hypergraph

Denial constraints only.

Vertices: facts in the original instance.

Edges: (minimal) sets of facts that violate some constraint.

Repairs: maximal independent sets.



Computing CQAs using the conflict hypergraph

[Ch., Marcinkowski, I&C, 2005].

Algorithm HProver:

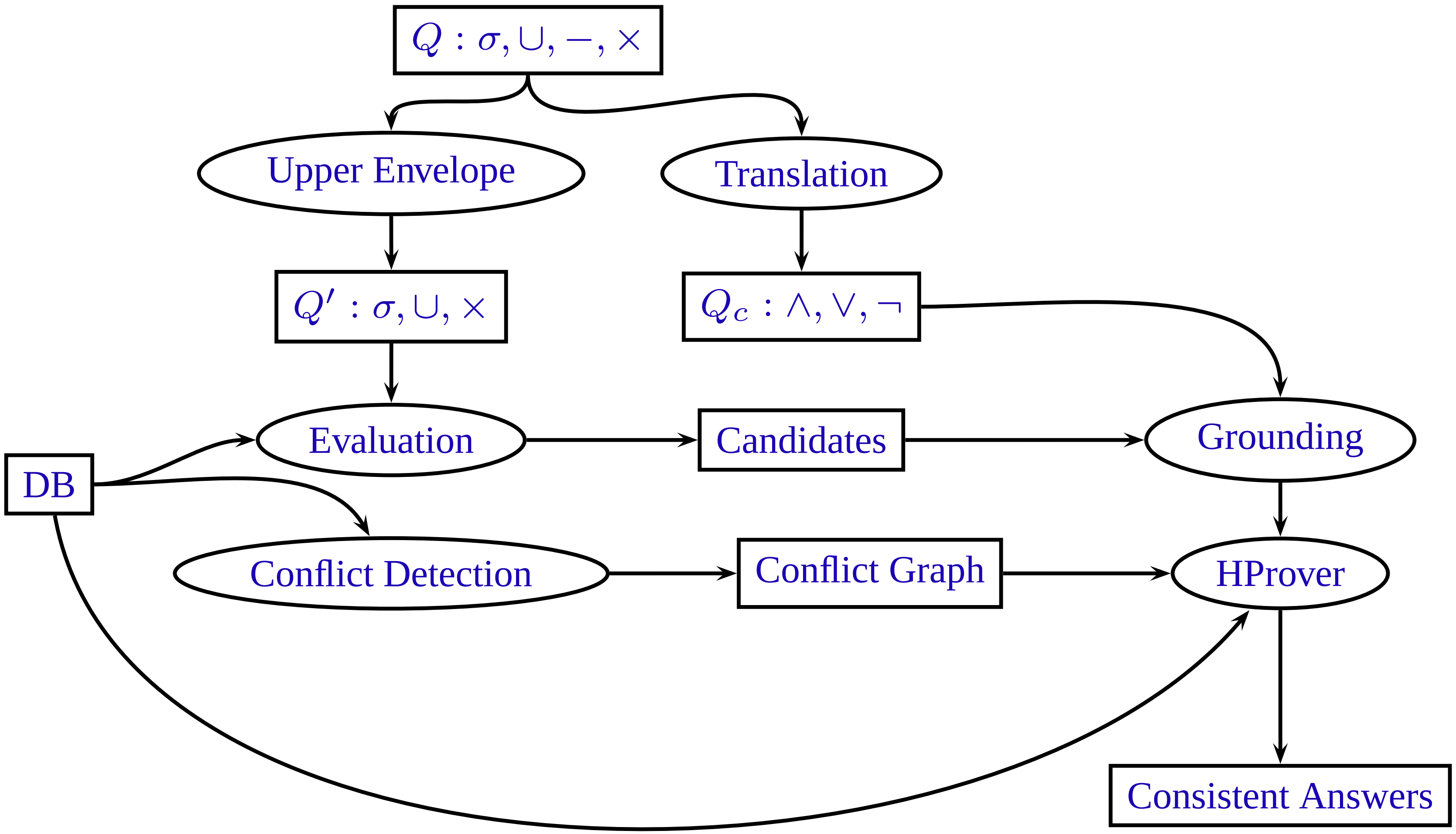
1. input: query Φ a disjunction of ground atoms
2. $\neg\Phi = P_1(t_1) \wedge \cdots \wedge P_m(t_m) \wedge \neg P_{m+1}(t_{m+1}) \wedge \cdots \wedge \neg P_n(t_n)$
3. find a repair including $P_1(t_1), \ldots, P_m(t_m)$ and excluding $P_{m+1}(t_{m+1}), \ldots, P_n(t_n)$ by enumerating the appropriate edges.

Excluding a fact A:

- A is not in the original instance, or
- A belongs to an edge $\{A, B_1, \ldots, B_k\}$ in the conflict hypergraph and $B_1, \ldots, B_k$ belong to the repair.

P (data complexity) for quantifier-free queries and denial constraints.

Hippo


$Q : \sigma, \cup, -, \times$
Upper Envelope
Translation
$Q' : \sigma, \cup, \times$
$Q_c : \wedge, \vee, \neg$
Evaluation
Candidates
Grounding
DB
Conflict Detection
Conflict Graph
HProver
Consistent Answers

Experimental results (Hippo)

[Ch., Marcinkowski, Staworko, CIKM’04].

The system Hippo:

- back-end: PostgreSQL
- conflict hypergraph (edges) in main memory
- optimization can eliminate many (sometimes all) database accesses in HProver
- tested for synthetic databases with up to 200K tuples, 2% conflicts
- computing consistent query answers using the conflict hypergraph faster than evaluating transformed queries
- relatively little overhead compared to evaluating the original query using the backend

Specifying repairs as logic programs

[Arenas, Bertossi, Ch., TPLP'03], [Greco, Greco and Zumpano, TKDE'03], [Barcelo, Bertossi, PADL'03], [Eiter et al., ICLP'03]:

- using logic programs with negation and disjunction
- repairs $\equiv$ answer sets
- several different encodings
- implemented using main-memory LP systems (`dlv`, `smodels`)
- Π_2^p-complete problems

Scope:

- arbitrary universal constraints, some inclusion dependencies
- arbitrary first-order queries

The approach of [Arenas, Bertossi, Ch., TPLP'03].

Facts:

$$Emp('\mathrm{B.Gates}', '\mathrm{Redmond\ WA}', 20\mathrm{K}).$$
$$Emp('\mathrm{B.Gates}', '\mathrm{Redmond\ WA}', 30\mathrm{K}).$$
$$Emp('\mathrm{A.Grove}', '\mathrm{Santa\ Clara\ CA}', 10\mathrm{K}).$$

Rules:

$$\neg Emp'(x,y,z) \vee \neg Emp'(x,y',z') \leftarrow Emp(x,y,z), Emp(x,y',z'), y \neq y'.$$
$$\neg Emp'(x,y,z) \vee \neg Emp'(x,y',z') \leftarrow Emp(x,y,z), Emp(x,y',z'), z \neq z'.$$
$$Emp'(x,y,z) \leftarrow Emp(x,y,z), not\ \neg Emp'(x,y,z).$$
$$\neg Emp'(x,y,z) \leftarrow not\ Emp(x,y,z), not\ Emp'(x,y,z).$$

Experimental data (INFOMIX)

[Eiter at al., ICLP'03].

The system INFOMIX:

- combines CQA with data integration (GAV)
- relational backend: PostgreSQL
- uses the disjunctive LP system `dlv` for repair computations
- optimization techniques: localization, factorization
- tested on legacy databases of up to 50K tuples.

Data complexity of consistent query answers

	Keys / primary keys)	Denial	Universal
$\sigma, \times, -$	P	P	P(binary)
$\sigma, \times, -, \cup$	P	P	?
σ, π	co-NPC / P	co-NPC	co-NP-hard
$\sigma, \times, \pi$	co-NPC / P(Ctree)	co-NPC	co-NP-hard

Tractable approaches:

- query rewriting
- conflict graphs

Sources: [Ch., Marcinkowski, I&C'05], [Fuxman, Miller, ICDT'05], [Cali, Lembo, Rosati, PODS'03].

Tractable/intractable queries

Tractable (P):

- under any denial constraints:

```
SELECT * FROM P
UNION (SELECT * FROM Q
       EXCEPT SELECT * FROM R)
```

Schema:

```
CREATE TABLE P(A PRIMARY KEY, B);
CREATE TABLE Q(C PRIMARY KEY, D)
```

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CREATE TABLE P(A PRIMARY KEY, B);
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```

Tractable (P):

```
SELECT Q.D
FROM  P, Q
WHERE P.B = Q.C
```

Schema:

```
CREATE TABLE P(A PRIMARY KEY, B);
CREATE TABLE Q(C PRIMARY KEY, D)
```

Tractable (P):

```
SELECT Q.D
FROM  P, Q
WHERE P.B = Q.C
```

Intractable (co-NP-complete):

```
SELECT Q.D
FROM  P, Q
WHERE P.B = Q.D
```

Alternative frameworks

Different assumptions about database completeness and correctness (in the presence of inclusion dependencies):

- possibly incorrect but complete: repairs by deletion only [Ch., Marcinkowski, I&C'05]
- possibly incorrect and incomplete: fix FDs by deletion, INDs by insertion [Cali, Lembo, Rosati, PODS'03].

Different notions of minimal repairs:

- minimal cardinality changes [Lopatenko, Bertossi, '06]:
  - tractability of incremental CQA:

    given a consistent database D and a fixed sequence of updates U, what is the complexity of computing CQA over $U(DB)$?

- repairing attribute values.

Attribute-based repairs

Several different approaches:

(A) ground and non-ground repairs [Wijsen, TODS'05]

(B) project-join repairs [Wijsen, FQAS'06]

(C) repairs minimizing Euclidean distance [Bertossi et al., DBPL'05]

(D) repairs of minimum cost [Bohannon et al., SIGMOD'05].

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(D) repairs of minimum cost [Bohannon et al., SIGMOD'05].

Computational complexity:

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

Project-join repairs

PJ-repairs: repairs of a lossless join decomposition.

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EmpDept

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

Functional dependencies:

$Name \rightarrow Dept$

$Dept \rightarrow Location$

Project-join repairs

PJ-repairs: repairs of a lossless join decomposition.

EmpDept

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

Functional dependencies:

$Name \rightarrow Dept$

$Dept \rightarrow Location$

Repairs:

John	Sales	Buffalo

Mary	Sales	Toronto

Decomposition

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

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John	Sales	Buffalo
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Decomposition

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

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

PJ-repairs:

John	Sales	Buffalo
Mary	Sales	Buffalo

John	Sales	Toronto
Mary	Sales	Toronto

Probabilistic framework for “dirty” databases

[Andritsos, Fuxman, Miller, ICDE’06].

Framework:

- 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

EmpSal

EmpName	*Salary*	prob
B. Gates	20M	0.7
B. Gates	30M	0.3
A. Grove	10M	0.5
A. Grove	20M	0.5

Functional dependency:

$EmpName \rightarrow Salary$

Query rewriting:

```
SELECT Name
FROM Emp
WHERE Salary > 15M
```

$\longmapsto$

```
SELECT Name, SUM(e.prob)
FROM Emp e
WHERE Salary > 15M
GROUP BY Name
```

Query rewriting:

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SELECT Name, SUM(e.prob)
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```

Evaluation of the rewritten query:

B. Gates	20M	0.7
B. Gates	30M	0.3
A. Grove	10M	0.5
A. Grove	20M	0.5

$\Rightarrow$

B. Gates	1
A. Grove	0.5

Further active topics

SQL queries:

- aggregation: glb/lub answers
- grouping

Data integration:

- GAV, LAV, GLAV,...
- tension between repairing and satisfying source-to-target dependencies

P2P:

- how to isolate an inconsistent peer

Nulls:

- repairs with nulls?
- clean semantics vs. SQL conformance

Priorities:

- preferred repairs
- conflict resolution

XML:

- what is an integrity constraint?
- what is a repair?
- minimum edit distance

Related work

Belief revision:

- revising database with integrity constraints
- revised theory changes with each database update
- emphasis on semantics (AGM postulates), not computation
- complexity results [Eiter, Gottlob, AI'92] do not quite transfer
- beyond revision: merging, arbitration

Disjunctive information:

- repair $\equiv$ possible world (sometimes)
- consistent answer $\equiv$ certain answer (sometimes)
- using disjunctions to represent resolved conflicts
- complexity results [Imielinski et al., JCSS'95] do not quite transfer

Lessons of CQA research

Need to tame the semantic explosion:

- different repair semantics overwhelm the potential user

More focus on applications:

- 99% technology, 1% applications
- often only repairing is needed
- heuristics

Integrate with other tools:

- schema matching/mapping
- data cleaning

The CQA community

Some data:

- over 30 active researchers
- 80–100 publications (since 1999)
- papers in major conferences (PODS, SIGMOD, ICDT, ICDE, CIKM, DBPL) and journals (TODS, TKDE, TCS, I&C, AMAI, JAL, TPLP)
- outreach to the AI community (qualified success)
- yearly workshop: IIDB (+LAAIC?)

Selected papers

1. M. Arenas, L. Bertossi, J. Chomicki, "Consistent Query Answers in Inconsistent Databases." PODS'99.
2. 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.
3. 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.
4. L. Bertossi, "Consistent Query Answering in Databases." SIGMOD Record, June 2006.