ERACER: A Database Approach for Statistical Inference and Data Cleaning

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SIGMOD 2010, Indianapolis

Problem

Real data is *dirty*

- Inconsistent, incomplete, corrupted, outdated, etc.
- Safety measures (e.g., constraints) are often not used
- Poor decisions based on dirty data costs billions annually

Data *cleaning* is hard

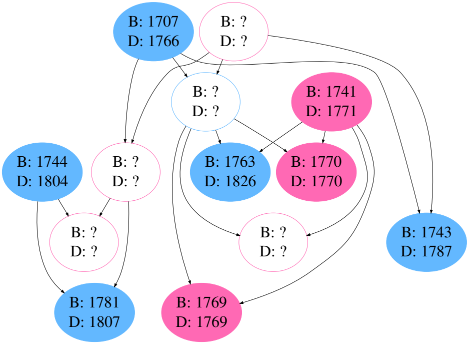
- Typically ad hoc, interactive, exploratory, etc.
- Uncertain process: what to do with the "errors?"
- Maintenance of results (e.g., lineage/provenance)
- Consumes large amount of data management time

(see Fan, Geerts, & Jia, VLDB 2008 tutorial)

Example 1: Genealogy Data

5M people from *Pedigree Resource File*

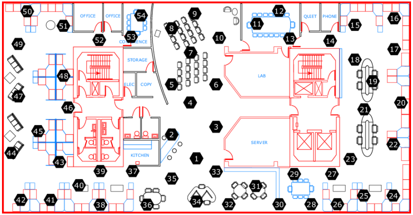
- `Person (ind_id, birth, death)`
- `Relative (ind_id, rel_id, role)`



Integrated from many sources, e.g.:

- Census records
- Immigration lists
- Family history societies
- Individual submissions

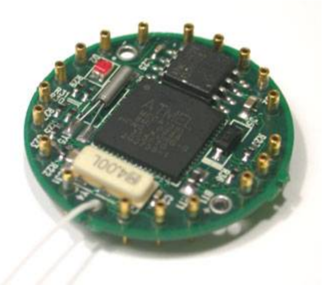
Example 2: Sensor Networks



- 54 sensors, every 31 seconds, for 38 days
- ≈ 18% obviously incorrect
- Multiple data types

2M readings of *Intel Lab Data*

- `Sensor (epoch, mote_id, temp, humid, light, volt)`
- `Neighbor (id1, id2, distance)`



Source: http://db.csail.mit.edu/labdata/labdata.html

Insight

Correlations *within* tuples, e.g.:

- Birth and death years
- Temperature and humidity values

Correlations *across* tuples, e.g.:

- Parents and children
- Neighboring sensors

Apply statistical relational learning

- Don't just clean tuples in isolation (e.g., functional dependencies)
- *Propagate* inferences multiple times

ERACER

Input:

- Possible tuple dependencies
- Correlation model skeleton

Output:

- PDFs for missing data
- Flags for dirty data

Baseline Approach:

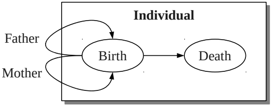
Bayesian networks

Exact inference (junction tree)

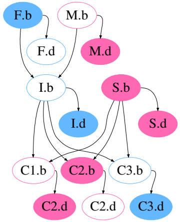
Bayes Net Toolbox for Matlab

Bayesian Network Formulation

Model *template* specifies conditional dependencies:



$\Longrightarrow$



Conditional probability distribution (CPD) at each node:

$P(I.d \mid I.b)$ *death year, given the birth year*

$P(I.b \mid M.b , F.b)$ *birth year, given parent birth years*

Prior distribution at nodes with no parents: $P(I.b)$

Simplified version of Relational Bayesian Networks (see e.g., Getoor & Taskar 2007)

Maximum Likelihood Estimation

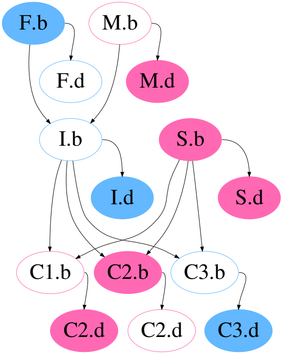
1. Learn CPDs from data, e.g.:

```
CREATE TABLE cpt_birth AS
  SELECT birth, death, count(*)
  FROM person
  GROUP BY birth, death;
```

2. Share CPDs across all nodes:

```
-- P(I.d | I.b = 1750)
SELECT death, count
FROM cpt_birth
WHERE birth = 1750;
```

3. Run inference (e.g., junction tree)
   - Construct Bayesian network
   - Bind evidence (query from DB)
   - Extract results (store in DB)



Challenges and Lessons Learned

Limiting model assumptions

- Fixed CPD structure (e.g., always two parents)
- Acyclicity constraint (can't model sensor data)

Potentially millions of parameters

- Becomes very inefficient
- Floating point underflow

Not scalable to large data sets

- DB may not fit into main memory
- Moving data in/out of R, Matlab, etc.

Not designed for data cleaning

- Propagates outliers/errors in original data
- Need to look beyond the *Markov blanket*

ERACER Approach:

Relational dependency networks

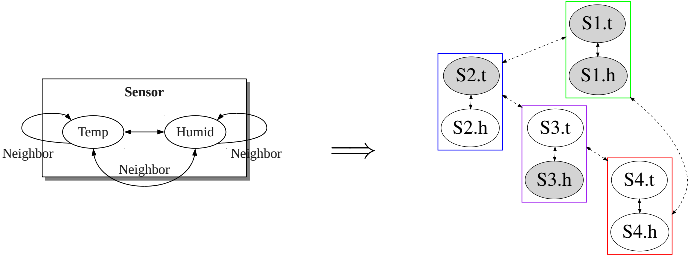
Approximate inference algorithm

SQL-based framework

Integrated data cleaning

Relational Dependency Networks

For example, at each sensor and time epoch:



In contrast to Bayesian networks, RDNs:

- *approximate* the full joint distribution
- learn CPDs locally based on *component models*
- allow *cyclic* dependencies (i.e., many-to-many)
- use *aggregation* to deal with heterogeneity

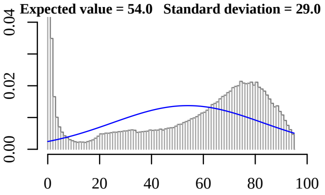
(see Neville & Jensen, JMLR 2007)

Component Models

Convolution (for genealogy)

- *parent age*: $M_{PA} = P(I.b - P.b)$
- *death age*: $M_{DA} = P(I.d - I.b)$

```
-- death age model
SELECT hist(death - birth)
FROM person;
```



Regression (for sensors)

- *mean temperature*:
  $S.t \sim \beta_0 + \beta_1 \cdot S.h + \beta_2 \cdot avg(N.t) + \beta_3 \cdot avg(N.h)$
- *mean humidity*:
  $S.h \sim \gamma_0 + \gamma_1 \cdot S.t + \gamma_2 \cdot avg(N.t) + \gamma_3 \cdot avg(N.h)$

ERACER Framework

Learning (one time, offline):

1. Extract graph structure using domain knowledge
2. RDNs aggregate existing data to learn parameters

Inference (multiple iterations):

3. Apply component models to *every* value in DB
4. Combine predictions to deal with heterogeneity
5. Evaluate posterior distributions for cleaning
6. Repeat 3–5 until happy (i.e., results converge)

Step 1: Extract Graphical Model

Construct nodes:

```
INSERT INTO node
  SELECT make_nid(epoch, mote_id), -- creates simple key
    new_basis(temp), new_basis(humid),
    new_basis(light), new_basis(volt)
  FROM sensor;
```

basis data type:

initial	original value, if any (e.g., *humid*)
pdf	current prediction (or distribution)
suspect	data cleaning flag (true = outlier)
round	when pdf/suspect was last updated

Construct edges:

```
INSERT INTO link
  SELECT make_nid(a.epoch, a.mote_id),
         make_nid(b.epoch, b.mote_id)
  FROM neighbor AS c -- e.g., within 6 meters
    INNER JOIN sensor AS a ON c.id1 = a.mote_id
    INNER JOIN sensor AS b ON c.id2 = b.mote_id
  WHERE a.epoch - 30 <= b.epoch
    AND a.epoch + 30 >= b.epoch;
```

Step 2: Learn RDN Parameters

Aggregate original data values:

```sql
CREATE TABLE learn AS
  SELECT
    -- individual instances
    min(expect(i.t)) AS ti, min(expect(i.h)) AS hi,
    min(expect(i.l)) AS li, min(expect(i.v)) AS vi,
    -- average neighbor values
    avg(expect(n.t)) AS tn, avg(expect(n.h)) AS hn,
    avg(expect(n.l)) AS ln, avg(expect(n.v)) AS vn
  FROM node AS i
    LEFT JOIN link AS l ON i.nid = l.id1
    LEFT JOIN node AS n ON l.id2 = n.nid
  GROUP BY i.nid;
```

Optional: apply noise filters, sample data, etc.

Estimate applicable component models

- Convolution: use built-in `hist` aggregate
- Regression: export to R; use `lm` function

Steps 3–6: Approximate Inference

For each round of inference:

1. Update predictions via the `erace` aggregate query
   - Infers/cleans all attributes in a single function call

```
SELECT erace(i, n)
FROM node AS i
  LEFT JOIN link AS l ON i.nid = l.id1
  LEFT JOIN node AS n ON l.id2 = n.nid
GROUP BY i;
```

   Key design choice: grouping by tuples, not attributes

2. Store results via `CREATE TABLE AS` (i.e., *propagation*)
   - Faster than `UPDATE` over the entire relation (MVCC)
   - Other optimizations possible (e.g., indexes on `nid`'s)

erace Aggregate Function

```
SELECT erace(i, n)
```

t_i	h_i
?	40%

t_n	h_n
21°	38%
35°	23%
24°	?

For each attribute in i:

- Select applicable model
- Apply/combine predictions
- Evaluate (cf. init and prev)

Data cleaning algorithm:

- Run inference for known values, as if missing
- Is original evidence within expected range?
- Replace outliers with inferred distributions
- Do not propagate suspects (rely on other data)

Many more details in the paper!

Experiments:

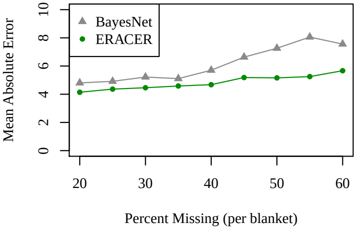
Generate synthetic populations

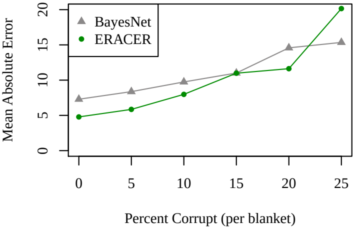
Randomly set attributes to NULL

Compare inferred values to original

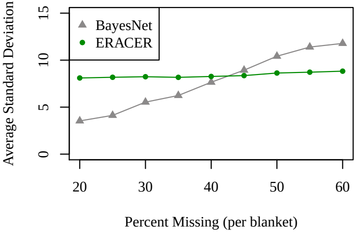
Genealogy Data Results

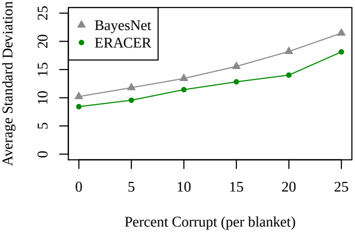
Accuracy of birth pdfs:





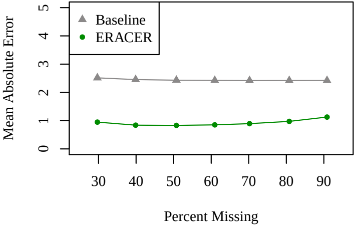
Variance (uncertainty):

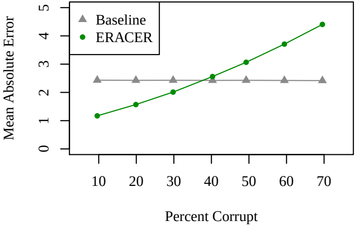




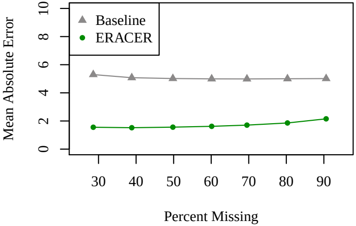
Sensor Data Results

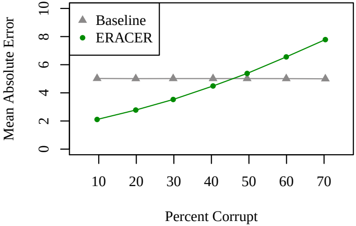
Accuracy of temperature pdfs:





Accuracy of humidity pdfs:





Summary

Database-centric approach for approximate inference

- Statistical framework for correcting errors
- Efficient; no need to move data to/from R/Matlab

Synergy of imputation and data cleaning tasks

- Additional evidence identifies errors more accurately
- Corrected data values improve the quality of inference

Empirical evaluation on two real-world data sets

- Similar accuracy to Bayesian network baseline
- Significant gains in runtime performance
- Added benefit of simultaneous data cleaning