B-HUNT: Automatic Discovery of Fuzzy Algebraic Constraints in Relational Data

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A Motivating Example

- Shipment data:

orderID	shipDate
2A5	2001-01-03
3C2	2001-04-15
3B8	2002-11-25
2E1	2002-10-31
3D6	2002-07-25
…	…

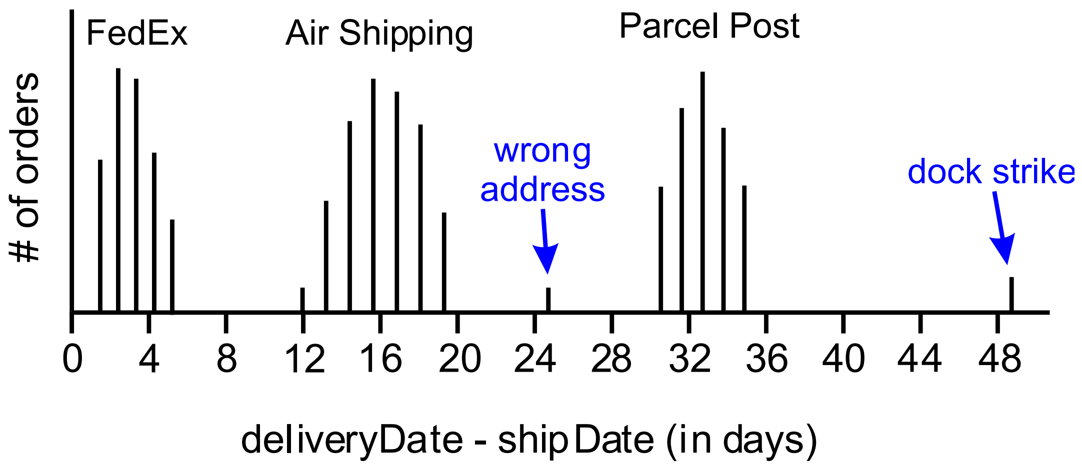
orders

orderID	deliveryDate	deliveryTime
2A5	2001-01-06	09:50
3C2	2001-04-27	13:00
3B8	2002-12-19	11:20
2E1	2001-12-02	16:10
3D6	2002-07-29	08:50
…	…	…

deliveries

Example: Fuzzy Constraints

SELECT DAYS(deliveryDate) – DAYS(shipDate)
FROM orders, deliveries
WHERE orders.orderID = deliveries.orderID



(deliveryDate BETWEEN shipDate + 2 AND shipDate + 5)	(25%)
OR (deliveryDate BETWEEN shipDate + 12 AND shipDate + 19)	(50%)
OR (deliveryDate BETWEEN shipDate + 31 AND shipDate + 35)	(25%)

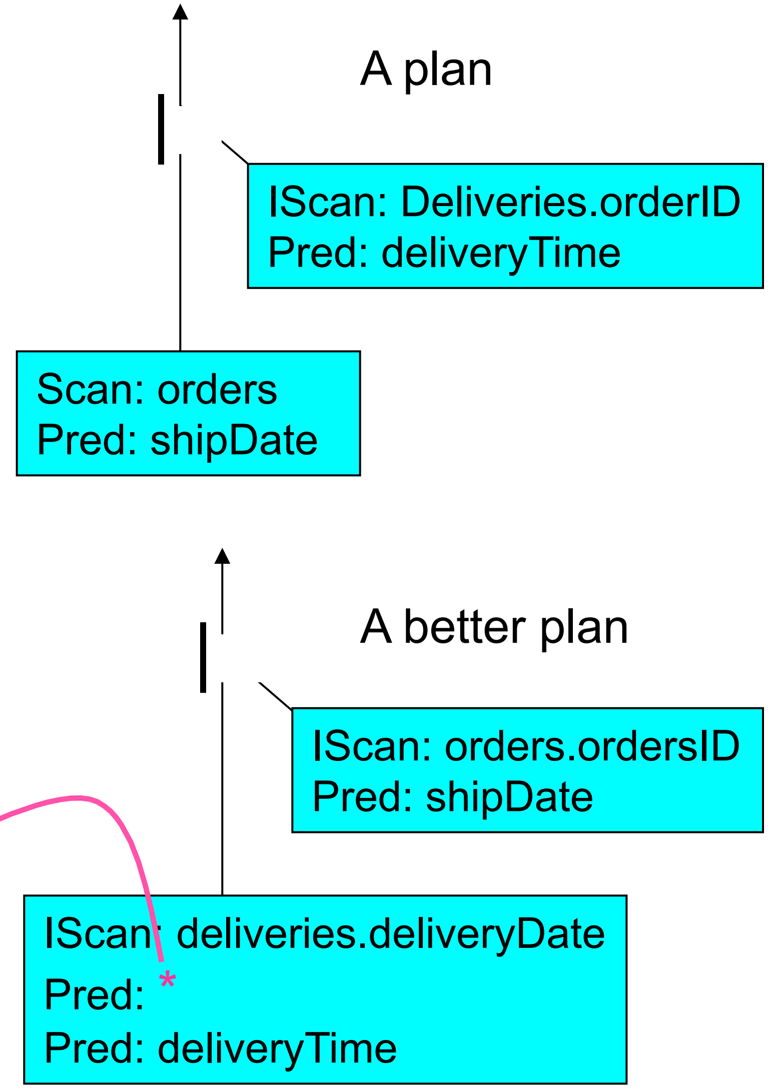
Exploiting the Constraints

SELECT COUNT(*) FROM orders, deliveries
WHERE shipDate = ‘2003-07-02’
AND deliveryTime > ’ 17:00’
AND orders.orderID = deliveries.orderID

Indexes:
  orders.ordersID,
  deliveries.orderID
  deliveries.deliveryDate
(NOT orders.shipDate)

Derived predicate:

(2003-07-04 [deliveryDate [2003-07-07)
OR (2003-07-14 [deliveryDate [2003-07-21)
OR (2003-08-02 [deliveryDate [2003-08-06)



Example 2: Partitioned Data

orderID	shipDate	deliveryDate
2A5	2003-01-03	2003-01-06
7D3	2003-01-17	2003-01-20
3C2	2003-04-15	2003-04-27
3B8	2003-06-19	2003-07-02
2E1	2003-06-16	2003-07-03
3D6	2003-08-25	2003-08-29
4D2	2003-09-12	2003-09-22

⋮

Horizontally range-partitioned

```
SELECT COUNT(*)
FROM orders
WHERE shipDate = '2003-07-01'
```

Derived predicate:

(2003-07-03 [deliveryDate [2003-07-10)
OR (2003-07-13 [deliveryDate [2003-07-24)
OR (2003-08-01 [deliveryDate [2003-08-05)

Fragment elimination!

B-HUNT Overview

- Automatic discovery of fuzzy algebraic constraints
- Why useful?
  - Query optimization (new plans, costing)
  - Advice on data partitioning, view/index creation
  - Constraints interesting in themselves
- Hidden constraints abound in real world
  - Unknown to application developer and DBA
  - Enforced by application but unknown to DBA
  - Known to DBA but not enforced due to high cost
  - Constraint is fuzzy, so not a standard DB “rule” per se

Fuzzy Algebraic Constraints

- Algebraic relationships: $a_1 \oplus a_2 \in I$
  - $\oplus$ is +, -, x, ÷, etc.
  - a_1, a_2 are attributes
  - I is subset of real numbers
- Pairing rule P
  - Determines which a_1 value goes with which a_2 value
  - Trivial pairing rule $\varnothing_R$ for table R:
    - a_1 value paired with a_2 value in same row of R
  - If attributes in different tables: P = join predicate
    - Self-joins OK also
- Algebraic constraint: $AC = (a_1, a_{2,}, P, \oplus, I)$

Algebraic Constraints, Continued

- Previous Example 1:
  - $a_1 =$ deliveries.deliveryDate, $a_2 =$ orders.shipDate
  - $\oplus$ is subtraction operator
  - P : 'orders.orderID = deliveries.orderID'
  - $I = \{2,3,4,5\} \cup \{12,13,\ldots,19\} \cup \{31,32,33,34,35\}$
- Previous Example 2: same as Example 1 except
  - $a_1 =$ orders.deliveryDate,
  - $P = \varnothing_{\text{orders}}$
- Focus on case where $I = I_1 \cup I_2 \cup \cdots \cup I_k$
  - The I_n's are disjoint "bump intervals" (of real line or integers)

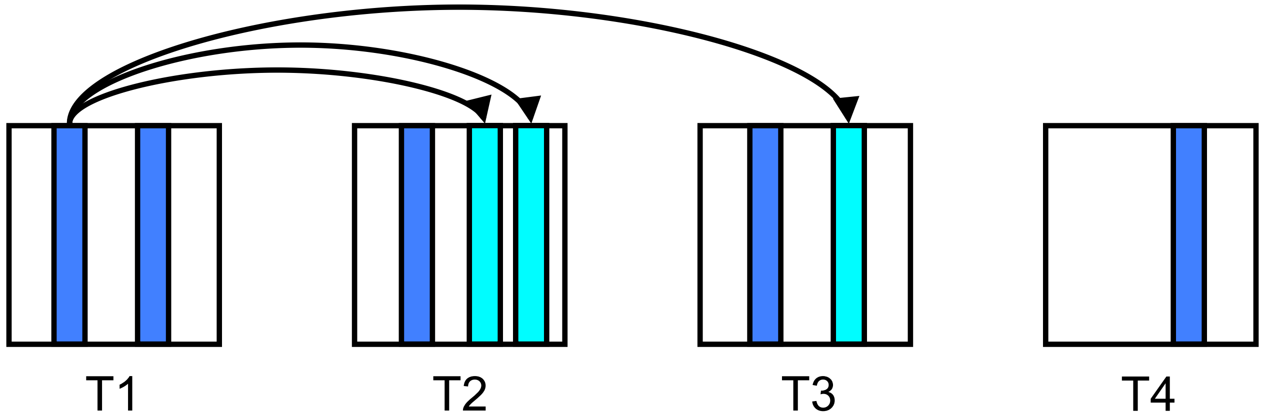
Outline of B-HUNT Algorithm

- Find *candidates* of form: $C = (a_1, a_2, P, \oplus)$
  - Find useful pairing rules
  - For each rule P find useful triples $(a_1, a_2, \oplus)$
- For each candidate, construct bump intervals
  - Based on sampled rows of (key) table
  - Use histogramming, segmentation, or clustering
  - Choose sample size to control # of *exceptions*

For query optimization:

- At load time: partition data into compliant + exceptions
- During query processing: combine results of
  - Running modified query that incorporates constraints
  - Running original query over (small) exception data

Candidate Generation: Pairing Rules



1. Generate trivial pairing rules: $\emptyset_{T1}, \emptyset_{T2}, \emptyset_{T3}, \emptyset_{T4}$
2. Generate set K of "key-like" attributes:

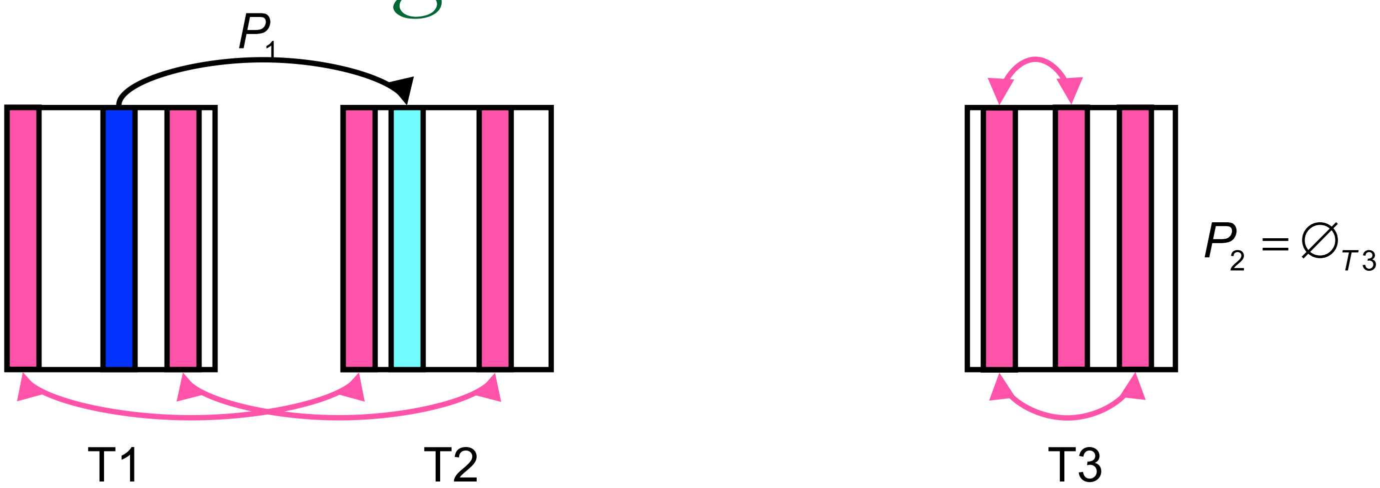
   declared primary and unique keys (and declared compound keys)

   attributes a such that $\#\text{rows}(a) \div \#\mathit{distinctValues}(a) \approx 1$
3. For each $a \in K$, add '$R.a = S.b$' to set of pairing rules iff
   - (i) a and b are of same datatype and either
   - (ii) (a,b) is declared (primary key,foreign key) pair; or
   - (iii) Every value in a sample from b has a match in a

Pruning the Pairing Rules

- Adjustable heuristic pruning criteria:
  - Trade off thoroughness and efficiency
  - For optimization: want pairing rules that
    - Lead to constraints with impact
    - Are easy to exploit at run time
    - Occur frequently in workload
- Examples: prune a pairing rule "$R.a = S.b$" if
  - R and S are "small" (no impact)
  - R or S has no index (hard to exploit)
  - $a \in K$ and $|S.b| / |R.a|$ is "small" (spurious relationship)
  - $S.b$ is a system-generated key (spurious relationship)

From Pairing Rules to Candidates



For each pairing rule, consider all attribute pairs (a_1, a_2) such that

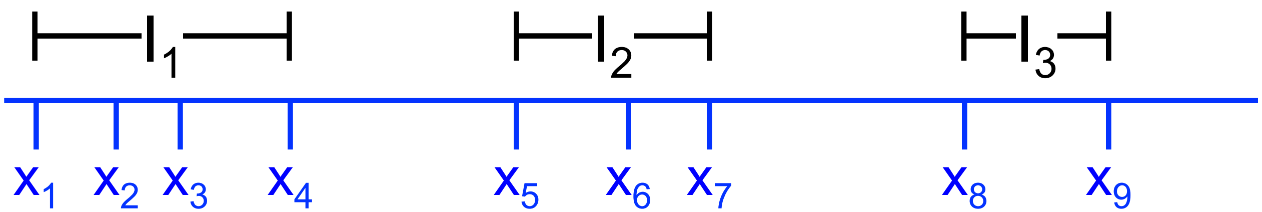
- a_1 and a_2 can be operated on by $\oplus$
- (a_1, a_2) not equal to attributes in pairing-rule join predicate

Prune candidate $(a_1, a_2, P, \oplus)$ if, e.g.,

- attributes have different data types
- too many NULL values
- either attribute lacks an index

Phrenology: Hunting the Bumps

- Each candidate $C = (a_1, a_2, P, \oplus)$ defines set of points Ω_C
- Bump hunt on *sample* of points from Ω_C
  - Because bump hunting must be scalable
- No exceptions in sample
  - I.e., segment the sample points



$L_1 = x_4 - x_1$ $L_2 = x_7 - x_5$ $L_3 = x_9 - x_8$

- Choose sample size to control # of exceptions in full DB

Direct “Optimal” Segmentation

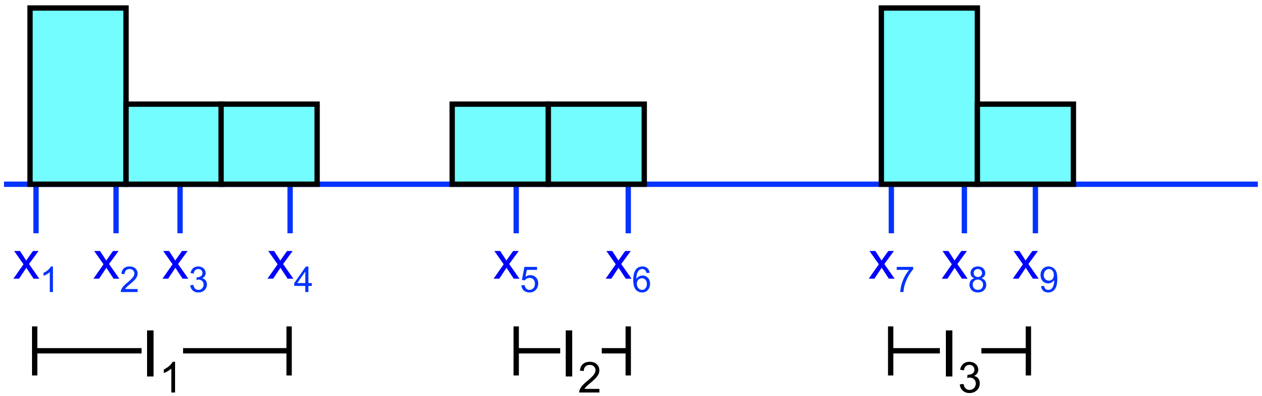
- Trade off filtering power and complexity

- Rough cost function (k = # intervals):

$$c(S) = \underbrace{wk}_{\text{complexity}} + (1-w)\underbrace{\left[\frac{1}{\Delta}\sum_{j=1}^{k} L_j\right]}_{\text{Filtering power}}$$

  - w is a weight between 0 and 1
  - Δ is estimated range of data values
- To minimize $c(S)$:
  - adjacent points in same segment iff $x_{i+1} - x_i < d^*$, where
    $d^* = \Delta\left(w/(1-w)\right)$
  - For discrete data types use $\max(d^*, 1+\varepsilon)$

Histogram-Based Segmentation



- Use $2h(n)$ buckets:
  - $h(n) = (2n)^{1/3}$ is "oversmoothing" lower bound
  - Minimizes asymptotic mean integrated squared error
  - Center an interval of length $2h(n)/\Delta$ around each isolated point

Choosing the Sample Size

- Uses approximate (conservative) estimate $n^*(k)$ of required sample size for a k-segmentation

$$n^*(k) = \frac{\chi^2_{1-p,2(k+1)}}{4f} + \frac{k}{2}$$

  - With probability p, fraction of exceptions is at most f
  - Uses theory of tolerance intervals (Tukey and Sheffé)
- Iterative procedure:

1. (Initialization) Set $k = 1$
2. Take sample of size $n \geq n^*(k)$
3. Compute constraint and observe number k' of bump intervals
4. If $n \geq n^*(k')$ then go to step 5, else set $k = k'$ and go to step 2
5. (Cleanup) Adjust for NULLs, Bernoulli fluctuations

Using the Constraints for Optimization

- Choose most important constraints (e.g. by filtering power)
- Partition data into “compliant” and “exception”
  - Physical partitioning or partial indexes
  - Table creation, e.g.:

```
CREATE TABLE exceptions(…);
INSERT INTO exceptions AS
(SELECT orders.orderID, deliveries.orderID,
  orders.shipDate, deliveries.deliveryDate,
  deliveries.deliveryTime
FROM orders, deliveries
WHERE orders.orderID = deliveries.orderID
AND NOT (
  (deliveryDate BETWEEN shipDate + 2 DAYS
   AND shipDate + 5 DAYS)
  OR (deliveryDate BETWEEN shipDate + 12 DAYS
   AND shipDate + 19 DAYS)
  OR (deliveryDate BETWEEN shipDate + 31 DAYS
   AND shipDate + 35 DAYS));
```

- Subsequent optimization builds on standard query processing technology

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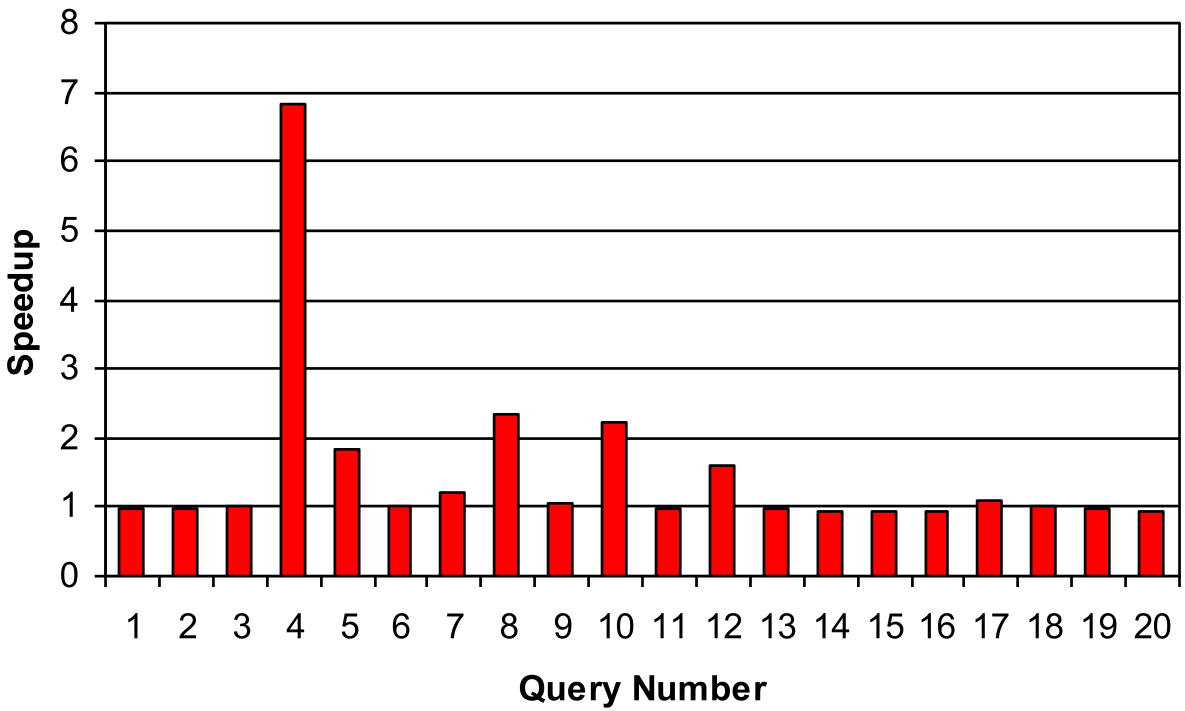
An Empirical Study

- The Database
  - 7 years of synthetic retail data
  - Similar to TPC-D schema
  - > 2.3 terabytes
  - Two largest tables exceed 13.8 billion and 3.45 billion rows
- Discovered constraints include:
  - $\text{t1.orderDate} \le t\text{2.shipDate} \le t\text{1.orderDate} + 4 \text{ MONTHS}$
  - $\text{t2.shipDate} \le t\text{2.receiveDate} \le t\text{2.shipDate} + 1 \text{ MONTH}$
- Time to discover constraints:
  - 4 minutes (in addition to ordinary statistics collection)
  - Versus hours or days for fancy mining methods

Empirical Study, Continued



- Improvement for 50% of the queries
- Significant improvement for 25%
- Best speedup: 6.8x (accesses to largest table reduced 100x)
- No significant performance decreases

Related Work

- Large literature on DB learning & relationship discovery
  - Query-driven methods (LEO, SITS, semantic constraints, etc.)
  - Data-driven methods (synopses, assoc. rules, reverse engrg.)
- Novel aspects of our work:
  - Fuzziness + algebraic rules + sampling + data-driven

Conclusions

- Fuzzy algebraic constraints are useful and interesting
- B-HUNT algorithm(s) for discovering such constraints
  - Highly automated
  - Fast (sampling based)
  - Robust to noisy data
  - Can lead to significant speedups in query processing
- A step towards smarter DBMS
- A useful framework for learning about data

Future Work

- Improvements
  - More extensive experimentation
  - More efficient techniques to enumerate pairing rules
    - Bell and Brockhausen
  - Exploitation of unique indexes, UNIQUE clauses in DDL, etc.
- Extensions
  - Apply to fuzzy functional dependencies
    - Bump at #(Honda) - #(Accord), not at #(Honda) - #(Camry)
  - Extend to XML repositories
  - Combine with query-driven technologies
    - Better pruning in B-HUNT
    - Avoid bad-warm-up and knowledge-phobic behavior of q-d

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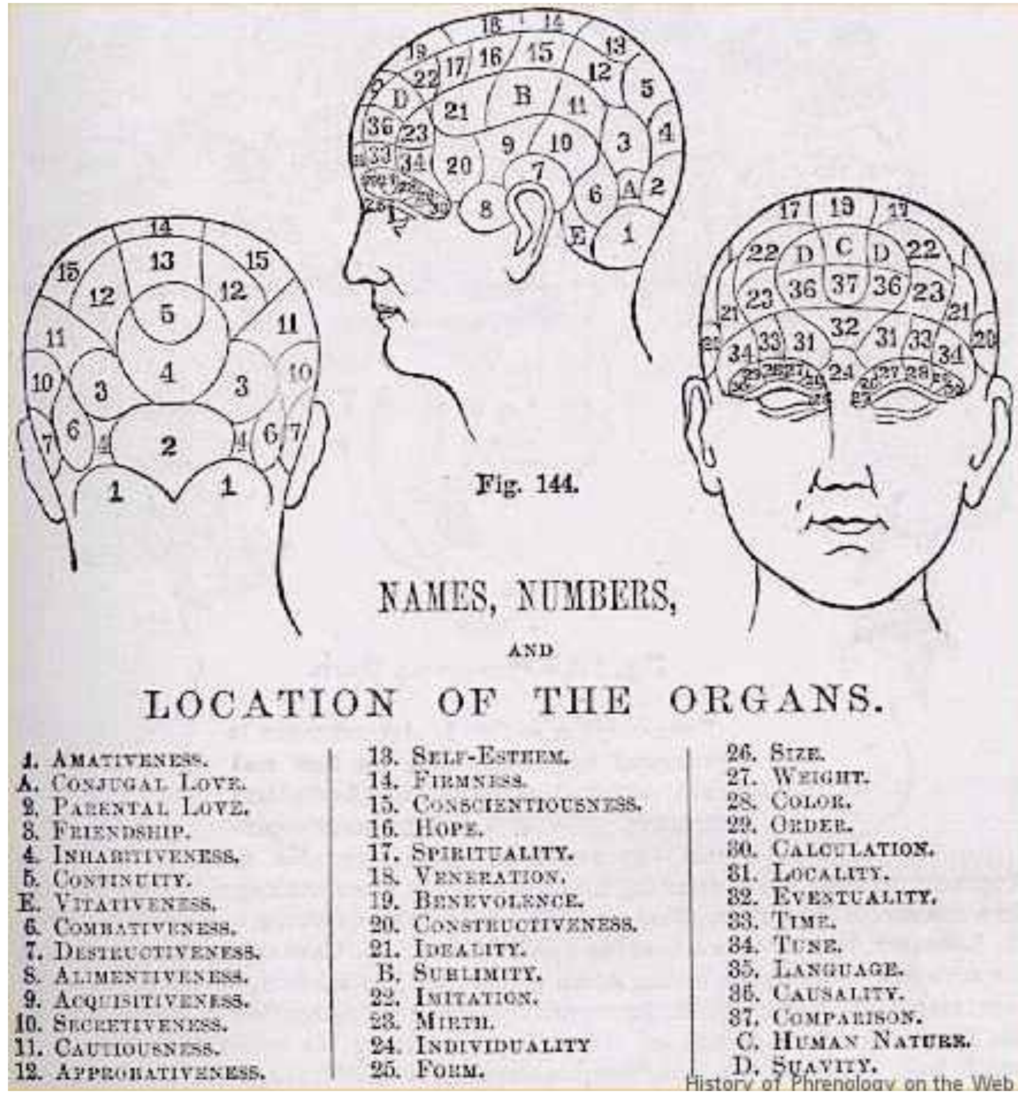
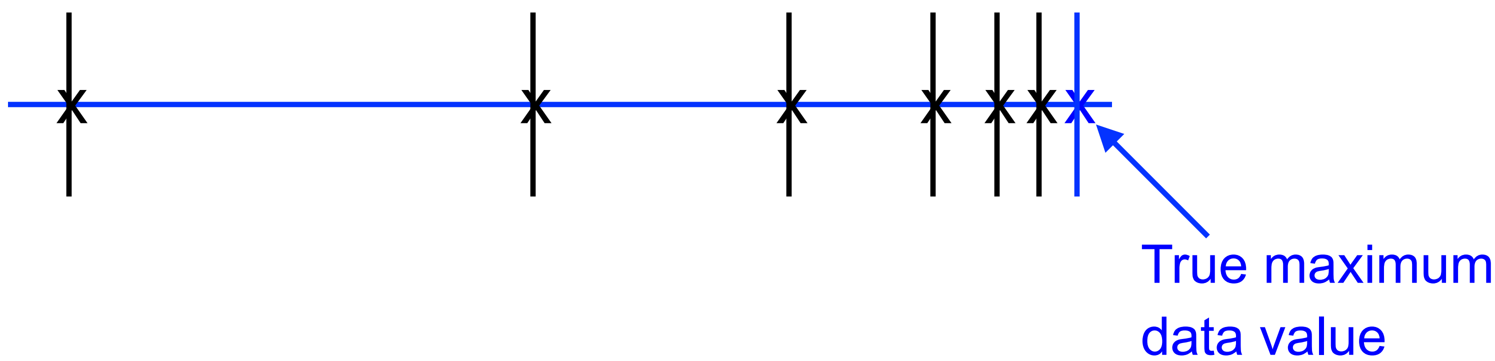


Extra Slides

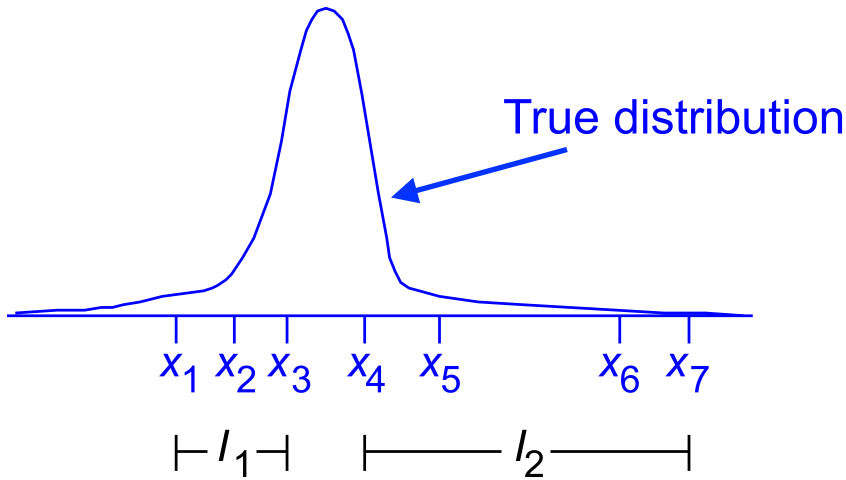
Correction for Real-Valued Data

- Expand endpoints by a few %
  - Merge overlapping intervals
  - Idea: deal with logarithmic rate of progress
  - Example: rightmost edge of rightmost bump interval



Computing the Estimate

- Look at straw man algorithm to get $n^*(k)$
  - Chooses a random *k*-segmentation of data points
  - Yields a conservative sample size



- Computing the required sample size
  - Related to quality control problems for manufacturing
  - Theory of tolerance intervals

Upper Bound, Continued

- Theorem: $\text{Prob}\{F > x\} \leq \text{Beta}(1-x; n-k, k+1)$
  - F is fraction of points in Ω_C that lie outside of k-segmentation
  - Beta is cumulative beta distribution function

$$\text{Beta}(t;\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \int_0^t u^{\alpha-1}(1-u)^{\beta-1}\, du$$

  - Proof uses several results of Tukey and Sheffé from 1940's
- To get sample size, solve: $\text{Beta}(1-f; n-k, k+1) = 1-p$
  - With probability at least p, exception fraction is at most f
  - Use Tukey and Sheffé approximation of Beta inverse:

$$n^*(k) \approx \frac{\chi^2_{1-p}}{4f} + \frac{k}{2}$$

    - χ^2_α is $100\alpha\%$ percentage point of χ^2 distribution with $2(k+1)$ degrees of freedom

Related Work

- Large literature on DB learning & relationship discovery
  - Query-driven methods
    - LEO learning optimizer [Stillger et al.]
    - SITS [Bruno and Chaudhuri]
    - Discovering semantic integrity constraints [Siegel, Yu & Sun]
  - Data-driven methods
    - Computation of synopses of multidimensional distributions
      - Histograms, wavelets, samples, Bayesian networks, etc.
    - Association rules, etc.
    - Mining functional and multi-valued dependencies
      - Reverse engineering (usually based on schema info)
      - Approximate functional dependencies [Huhtala et al.]
- Novel aspects of our work:
  - Fuzziness + algebraic rules + sampling + data-driven