TOC

INDEX

VIEW

B16 Speeding Up DB2 UDB Using Sampling

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It is becoming increasingly difficult to process the massive amounts of data stored in modern data warehouses and on the Web. Executing queries on samples of the data rather than on the entire database can speed up data processing by orders of magnitude. This talk is about how to exploit sampling in DB2 UDB, now and in the future. After reviewing basic sampling concepts, we give examples of business problems for which sampling is beneficial. We then describe sampling techniques and tricks that can be used in current versions of DB2 UDB, either to materialize a sample that can be subsequently used for mining or auditing purposes, or to provide quick approximate answers to aggregation queries, along with quality estimates. Next, we discuss the proposed ISO syntax for sampling in SQL queries, and describe a prototype version of DB2 UDB that supports this functionality. Finally, we discuss how sampling can facilitate real-time exploration of massive datasets.

B16

Speeding up DB2 UDB Using Sampling

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IBM Data Management Technical Conference

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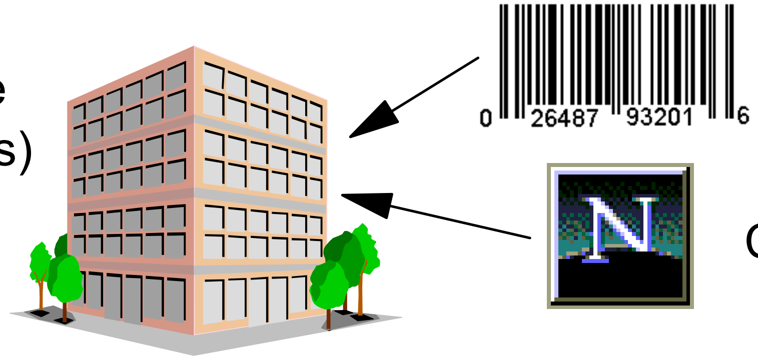
RETURN TO INDEX

The Challenge: Massive Data Volumes

- Online data volume is growing faster than Moore's law



Data Warehouse
(100's of Terabytes)

Swipe-stream data

Click-stream data

sensor data?

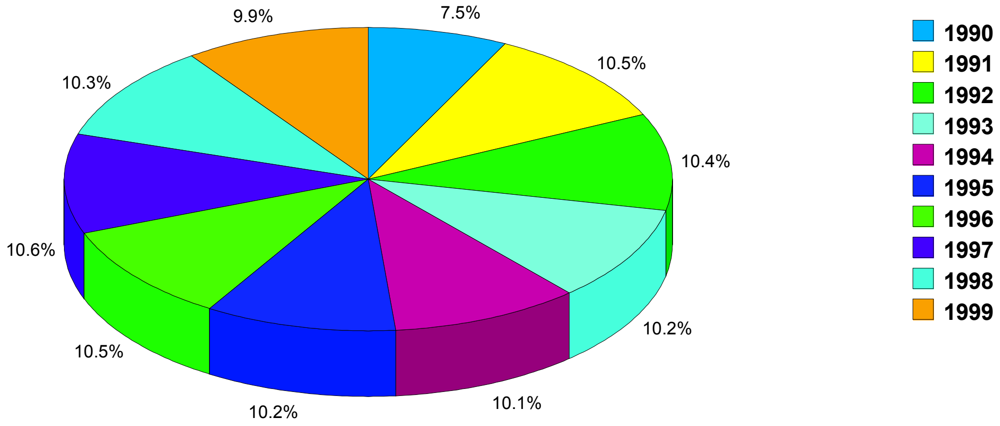
- Users want to run:
  - BI queries / OLAP queries
  - Advanced analytical/mining/statistical algorithms
  - Exploratory/interactive analyses ("fishing expeditions")

- A big problem:
  - Many algorithms don't scale with increasing data volume
  - Fishing expeditions infeasible

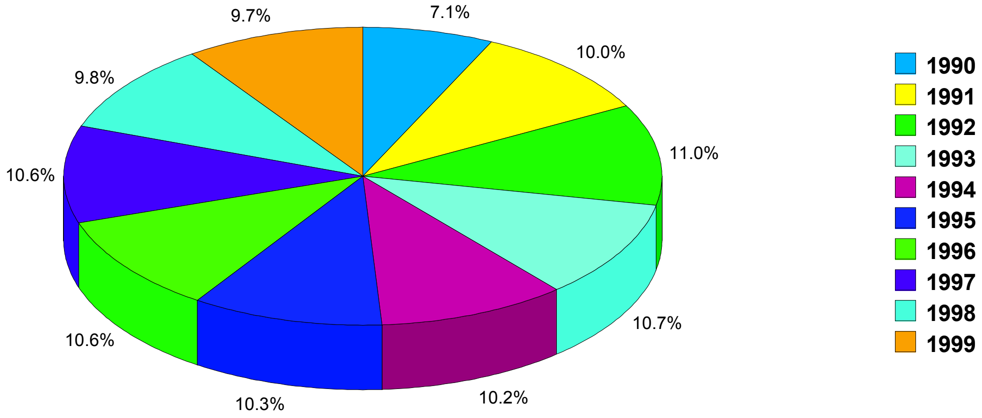
Solution: Sampling

- Processing less data => huge performance improvement
- Approximate answers often suffice

No Sampling (25 min.)

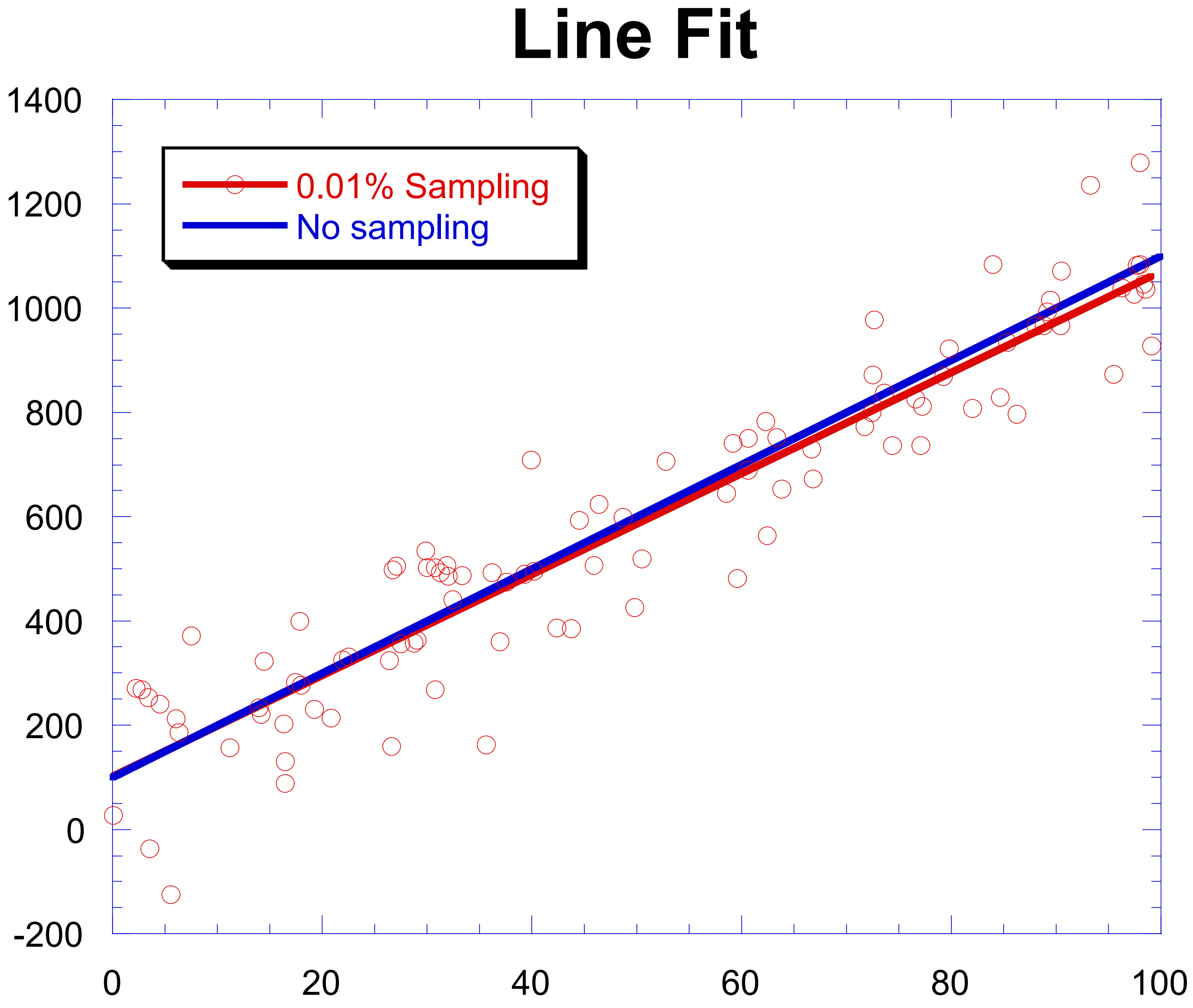


1% sampling (2 sec)



Sampling for Scalable Analytics

- Example: Linear regression on a million-row table



Main Uses of Database Sampling

- Quick approximate answers to aggregation queries

```
SELECT AVG(sales) FROM salesdata
GROUP BY year
```

- Quick approximate answers to analytical queries

```
SELECT REGR_SLOPE(sales, ad_budget),
       REGR_ICPT(sales,ad_budget)
FROM ad_campaign_data
```

- Compressed representation of dataset
  - For auditing
  - For "fuzzy exploration"
  - For input into mining/analysis applications

Road Map

- Basic database sampling schemes
- Sampling in DB2 V7.1 and earlier
- The proposed ISO sampling standard
- Sampling support in DB2 V8
- Combining sampling and SQL
- Some research directions

Database Sampling Schemes

- Focus on a single table

- We want to construct a sample (subset) of the rows
  - Often want "representative" subset of rows
  - Often formed using a probabilistic selection process
  - Sometimes want more of certain types of rows than others

- Close connection between sampling and estimation methods
  - Estimation formulas need to take sampling scheme into account
  - Often want measure of precision of estimate
    - Standard error: measures variability of an estimate

Large-table results:

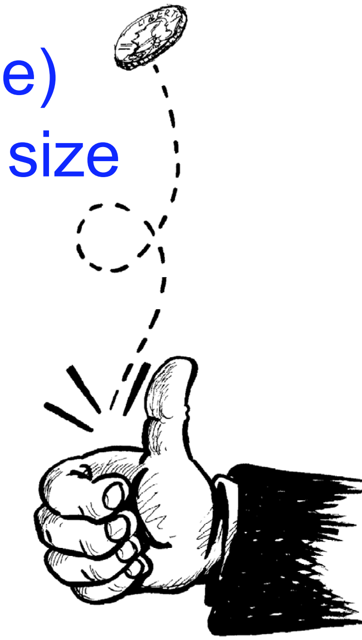
----

within +/- 1.96 SE's: 95%
within +/- 2.58 SE's: 99%

Row- Level Bernoulli Sampling

- "Coin flip" sampling
  - Flip a weighted coin for each row (independently)
  - Include row into sample if coin is "heads"
  - Probability of "heads" is called the "inclusion probability"
  - Each row in the table is equally likely to be included

- Sample size is random
  - Expected size = (inclusion probability) * (population size)
  - With high probability, actual size within ±q of expected size
    - $q != 2 (Np(1-p))^{1/2}$
      (p = inclusion probability and N = population size)
    - ex: N = 1,000,000, p = 1/2

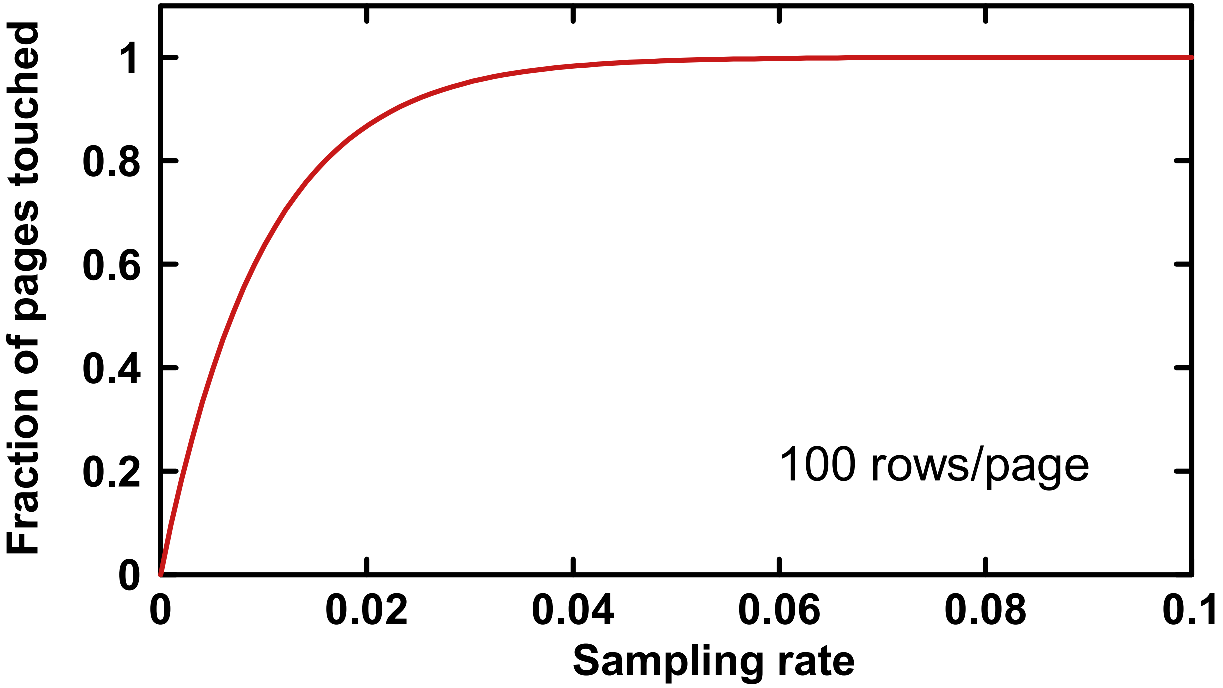


actual size within 0.2% of expected size
with high probability

Row-Level Bernoulli Sampling (Cont'd)

- Advantages:
  - Integrates well with SQL (treat sampling clause as a predicate)
  - Easy to parallelize

- Disadvantage: High I/O cost
  - Naive implementation: touch every page
  - Clever implementation: touch (almost) every page



Page-Level Bernoulli Sampling

- Sample pages first
  - Flip a coin for each page
  - Use all rows on a page

- Unlike row-level, inclusion of rows is not independent

- Advantage: Dramatic I/O savings
  - More efficient use of rows on pages touched
  - Quick algorithms for generating page lists
  - Can exploit prefetching

The Fly in the Ointment: Clustering

- What if data values are clustered on pages?

1 100 1 100
100 100 1 1
1 100 100 1
100 1 100 1

Table 1 (Unclustered)

vs

1 1 1 1
1 1 1 1
100 100 100 100
100 100 100 100

Table 2 (Clustered)

- Example: Take 50% sample of Table 2 to estimate the sum
  - Estimator: 2 x (sum of numbers in sample)
  - Row-level sampling: average value = 808 and SE = 283
  - Page-level sampling: average value = 808 and SE = 566
  - Estimated SE if page-level treated as row-level: 242 (on avg)

- Moral of the story:
  - Both methods yield correct answer on average (unbiased)
  - Page-level sampling has twice the error for clustered data
  - Must use correct formula to estimate the SE (false optimism)

Clustering: What's Going On?

- Q: Why is page-level samping less precise (though much cheaper) than row-level sampling when the data is clustered?

- A1: What you see is more dependent on luck-of-the-draw
  - E.g., sum = 4 versus sum = 400

- A2: Not much information from a sampled page
  - First row contains most of the information
  - Rest of rows "wasted"
  - Want to see a lot of pages (i.e., row level sampling)

- Issue: Detecting clustering (will discuss later)

Simple Random Sampling (SRS)

- Sample size *n* is deterministic and prespecified

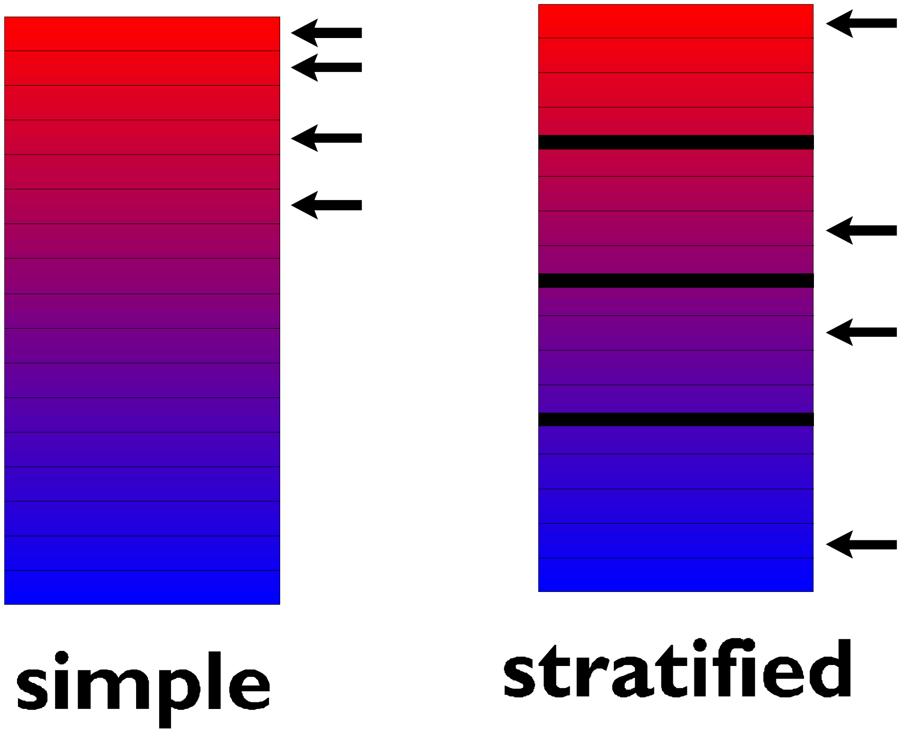
- Each sample of size *n* is equally likely

- Conceptually, to create a SRS:
  - Choose first row r1 randomly + uniformly from table T
  - Choose r2 randomly + uniformly from T - {r1}
  - Choose r3 randomly + uniformly from T - {r1,r2}
  - etc.

- Can also choose with replacement (SRSWR)

Stratified Sampling

- Reduces "bunching up" due to luck-of-the-draw



- Data values within strata should be similar
  - "If you've seen one, you've seen 'em all"

Cluster Sampling

- Population members grouped into disjoint clusters
- Sample clusters at random (Bernoulli or SRS or ...)
- Include every member of a sampled cluster into final sample
- Ex: Page-level Bernoulli sampling (cluster = page)
- Ex: Sample of customer transactions
  - Sample customers at random
  - Include all transactions for each sampled customer

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  - Integrating sampling and analytics
  - Interactive querying

Row-Level Bernoulli Sampling

- Use RAND() function dynamically
  - RAND returns a random number between 0 and 1
  - Ex: let :samp_rate be a host variable (e.g., samp_rate = 0.01)

```
SELECT loc.country AS country, year(t.pdate) AS year,
  sum(ti.sales) / :samp_rate AS est_sales,
FROM trans t, transitem ti, loc loc
WHERE t.transid = ti.transid AND loc.locid = t.locid
      AND rand() < :samp_rate
GROUP BY loc.country, year(t.pdate)

country    year  est_sales
--------  ------  ----------
     USA    1998      127505
     USA    1999      236744
GERMANY     1998       86278
GERMANY     1999      126737
   ...
```

Need to scale up query result

- Problem: High I/O cost (as always)

Simple Random Sampling

- Append column of random numbers to table

```
ALTER TABLE mytable ADD COLUMN randnum DOUBLE;
UPDATE mytable SET randnum = RAND();
```

- Can obtain multiple, disjoint SRS's
  - Ex: An SRS of 100 rows

```
WITH dt AS (SELECT c1,...,cN,
              ROWNUMBER() OVER (ORDER BY randnum) AS num
            FROM mytable)
SELECT c1,...,cN FROM dt
WHERE num >= 500 AND num < 600
```

- Can cluster by randnum on disk to amortize cost
  - Sample = scan
  - Degrades performance of other queries
  - Refresh is expensive

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The Proposed ISO Sampling Standard

- Can place sampling clause after any SQL table reference

```
SELECT *
FROM t1 TABLESAMPLE BERNOULLI(10.0)
WHERE ...
```

- General form of sampling clause

TABLESAMPLE <sampling_method>(<p>) REPEATABLE(<n>)

  - <sampling_method> is
    - BERNOULLI: row-level Bernoulli sampling
    - SYSTEM: vendor-defined (efficient) sampling method
  - <p> = inclusion probability for each row (%)
    = (expected) sampling fraction

ISO Sampling Standard (Cont'd)

- REPEATABLE(<n>) clause
  - Same result at each query execution provided <n> is fixed
  - Example (row-level sampling):
    - REPEATABLE(3): r56, r107, r3, ... every time
    - REPEATABLE(48): r2002, r5, r86, ... every time
  - Used for debugging and testing
  - Need only be provided on "best effort" basis
    - Parallelism is an issue

ISO Sampling Standard (Cont'd)

- Argument to <sampling method> can be an expression
  - Ex: I want about 1000 rows from t1 but don't know size of t1

```
SELECT * FROM t1
    TABLESAMPLE BERNOULLI(1000 / (SELECT COUNT(*) FROM t1))
```

- Argument to REPEATABLE also can be an expression

ISO Sampling Semantics

- Sample each table, then execute rest of query

- Ex: Select employees with salary > (estimated dept. average)

```
SELECT name, salary FROM emp e
WHERE salary > (SELECT AVG(salary)
                FROM emp e1 tablesample bernoulli(1.0)
                WHERE e1.deptno = e.deptno
               )
```

- Estimated salary is fixed for each department
  - Within a single query execution
  - Because e1 is sampled only once
  - Values vary for different executions unless REPEATABLE
  - Can override by using REPEATABLE with computed arg

Some Unresolved Standards Issues

- Scaleup issues
  - Ex: query to estimate total sales in $

```
SELECT SUM(ti.qty * ti.price) / .01 AS amount
FROM  stars.transitem1 as ti TABLESAMPLE BERNOULLI(1)
```

  - Values of SUM, COUNT, etc. are for rows retrieved
  - Need scale-up functions to extrapolate these to entire database
  - Can be nontrivial: COUNT(DISTINCT)
  - No consensus on standards for expressing scaleup

- Error estimates
  - User must provide own formulas or UDFs for std error etc.
  - Separate formula/UDF needed for each aggregate in SELECT
  - No consensus yet on syntax

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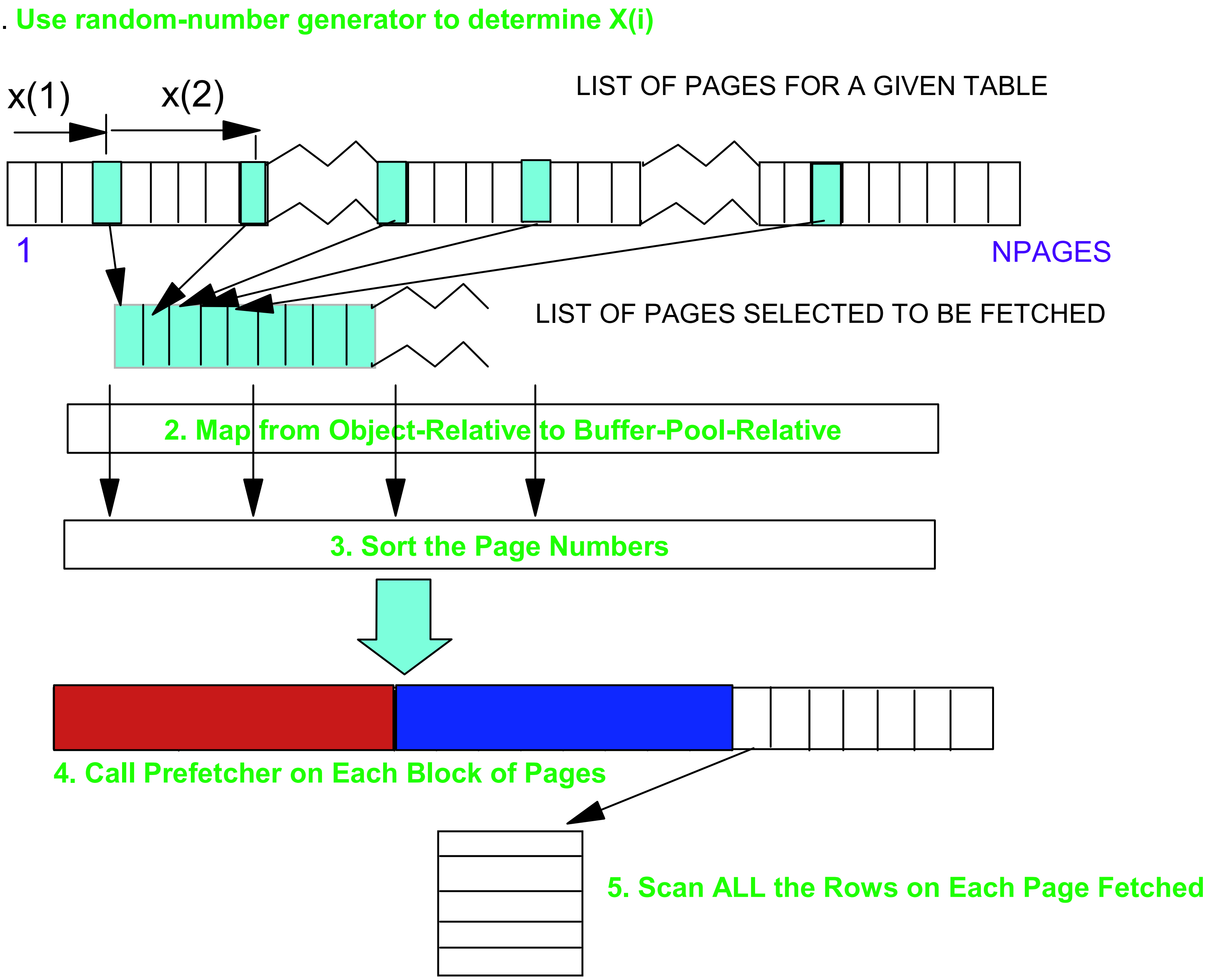
DB2 V8 Support of ISO Standard

- Currently scheduled for a V8 Fixpack
- BERNOULLI: Fully implemented (MPP parallizable)
- SYSTEM: Implemented as page-level Bernoulli sampling
- Current limitations
  - Can only sample from materialized tables
  - Only simple expressions as args to <sampling_method>
  - Only simple integer expressions as args to REPEATABLE
  - SMP parallelism not exploited
  - REPEATABLE is still best effort
    - OK in non-parallel setting (If data, partitioning, etc. unchanged)

Page-Level Sampling: What's Going On?



1. Use random-number generator to determine X(i)

x(1)
x(2)
LIST OF PAGES FOR A GIVEN TABLE
1
NPAGES
LIST OF PAGES SELECTED TO BE FETCHED

2. Map from Object-Relative to Buffer-Pool-Relative

3. Sort the Page Numbers

4. Call Prefetcher on Each Block of Pages

5. Scan ALL the Rows on Each Page Fetched

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Combining Sampling and SQL

- Greatly enhances power of sampling

- Applications
  - Quick approximate analytics
  - Quick approximate answers to aggregation queries
    - Precision measures (standard error)
  - Other sampling schemes
  - Drill-down in "fuzzy" OLAP cubes

Quick Approximate Analytics

- Ex: Linear regression

```
SELECT REGR_SLOPE(sales, ad_budget),
       REGR_ICPT(sales,ad_budget)
FROM ad_campaign_data TABLESAMPLE SYSTEM(10.0)
```

- For other examples see Session B15

- Of course, can also feed sample into SAS, IntelligentMiner, etc.

Standard Error: Row-level Sampling

- Ex: Sample from single table to estimate total sales

```
SELECT sum(sales) / :samp_rate AS est_sales,
  SQRT((1e0/:samp_rate)*((1e0/:samp_rate)-1e0)*sum(sales*sales)) AS std_err
FROM transactions TABLESAMPLE BERNOULLI(100 * :samp_rate)

est_sales  std_err
---------  -------
   146821  1225.61
```

- Ex: Same as above, but for average sales (can add predicate)

```
WITH dt AS
 (SELECT COUNT(*) / :samp_rate as est_count,
         SUM(sales) / COUNT(*) AS est_avg,
         (1e0/:samp_rate)*((1e0/:samp_rate)-1e0)*SUM(sales*sales) AS v_sum,
         (1e0/:samp_rate)*((1e0/:samp_rate)-1e0)*COUNT(*) AS v_count,
         (1e0/:samp_rate)*((1e0/:samp_rate)-1e0)*SUM(sales) AS cov_cs
  FROM transactions TABLESAMPLE BERNOULLI(100 * :samp_rate))
SELECT est_avg,
       SQRT(v_sum-2e0*est_avg*cov_cs+est_avg*est_avg*v_count)/est_count
         AS std_err
FROM dt;
```

A More Precise Estimator

- Bernoulli sampling as before (but scaleup is different)

```
WITH
  dt1 AS (SELECT COUNT(*) AS big_count FROM transactions),
  dt2 AS (SELECT AVG(sales) AS avg_sales,
                 count(*) as count_sales,
                 var(sales) AS var_sales
          FROM transactions TABLESAMPLE BERNOULLI(100 * :samp_rate))
SELECT avg_sales * big_count AS est_sales,
big_count * sqrt( ((1e0 - :samp_rate)/count_sales)
  * (1e0 - (1e0/count_sales)) * (count_sales/(count_sales-1e0))
  * var_sales) AS std_err
FROM dt1, dt2
```

scaled up by
true sampling rate

SE Formulas for Row-Level Sampling in Complicated Queries

- Can sometimes use single table formulas

```
SELECT loc.country AS country, year(t.pdate) AS year,
  sum(ti.sales) / :samp_rate AS est_sales,
  sqrt((1e0/:samp_rate)*((1e0/:samp_rate)-1e0)*sum(sales*sales)) AS std_err
FROM trans t, transitem ti TABLESAMPLE BERNOULLI(100 * :samp_rate), loc loc
WHERE t.transid = ti.transid AND loc.locid = t.locid
GROUP BY loc.country, year(t.pdate)
```

```
country    year  est_sales  std_err
-------  ------  ---------  -------
    USA    1998     127505  1326.09
    USA    1999     236744  2133.17
GERMANY    1998      86278   961.45
GERMANY    1999     126737  1488.66
...
```

- But be careful!! Alternative SE formulas needed for
  - Sampling from `trans` table (cluster sampling)
  - Sampling from both tables
  - etc.

Standard Error: Page-level Sampling

- Ex: Sample from single table to estimate total sales
  - Use SAMPLE_UNIT_ID() to get page number of sampled row
  - Argument is any column in sampled table
  - (Not in standard yet, but proposed for DB2 release)

```
WITH
  dt1 AS (SELECT sales FROM transactions TABLESAMPLE
SYSTEM(100*:samp_rate)),
  dt2 AS (SELECT SUM(sales) AS s_sales
          FROM dt1
          GROUP BY SAMPLE_UNIT_ID(sales)),
  dt3 AS (SELECT SUM(s_sales*s_sales) AS ss_sales,
                 SUM(s_sales) AS tot_samp_sales
          FROM dt2)
SELECT tot_samp_sales / :samp_rate AS est_sales,
  SQRT((1e0/:samp_rate)*((1e0/:samp_rate)-1e0)*ss_sales) AS std_err
FROM dt3;
```

SE for Average Sales (Page-Level Version)

```
WITH
  dt1 AS (SELECT SUM(sales) AS s_sales, COUNT(*) AS c_sales
          FROM transactions TABLESAMPLE SYSTEM(100*:samp_rate)
          GROUP BY SAMPLE_UNIT_ID(sales)),
  dt2(est_count, est_avg, v_sum, v_count, cov_cs) AS
    (SELECT SUM(c_sales) / :samp_rate,
            SUM(s_sales) / SUM(c_sales),
            (1e0/:samp_rate)*((1e0/:samp_rate)-1e0)*SUM(s_sales*s_sales),
            (1e0/:samp_rate)*((1e0/:samp_rate)-1e0)*SUM(c_sales*c_sales),
            (1e0/:samp_rate)*((1e0/:samp_rate)-1e0)*SUM(s_sales*c_sales)
     FROM dt1)
SELECT est_avg,
       SQRT(v_sum-2e0*est_avg*cov_cs+est_avg*est_avg*v_count)/est_count
         AS std_err
FROM dt2
```

Detecting Clustering

- Ex: Kruskal-Wallis Test (on sample of 10-50 pages)
  - Works for any data that can be ordered

```
WITH dt1 AS (SELECT t.c1, SAMPLE_UNIT_ID(c1) AS p_no
             FROM t TABLESAMPLE SYSTEM(1)),
     dt2 AS (SELECT p_no,
                    rank() over (order by c1) AS c_rank
             FROM dt1),
     dt3 AS (SELECT AVG(c_rank) AS avg_rank,
             COUNT(*) AS p_size
             FROM dt2
             GROUP BY p_no),
     dt4 AS (SELECT SUM(p_size*avg_rank*avg_rank) AS xsum,
                    COUNT(*) AS num_pages
             FROM dt3),
     dt5 AS (SELECT COUNT(*) AS ssize FROM dt1)
SELECT (12e0/((ssize)*(ssize+1e0)) * xsum
           - 3e0*(ssize + 1e0) AS KW,
       num_pages
FROM dt4, dt5
```

- Let δ^2 be a chi-squared random with (num_pages - 1) d.f.
- If Prob(δ^2 > KW) is close to 0, then c1 is clustered

Detecting Clustering: Example

- Parameters
  - 50,000 rows with 50 rows per page (50 pages in sample)
  - Real values between 0 and 5000

- Table A: Values randomly assigned to pages
  - KW = 40
  - Prob(δ^2 > 40) = 0.84

- Table B: Values perfectly clustered
  - KW = 2542
  - Prob(δ^2 > 2542) << 0.005

- Caveats
  - Ties must be handled specially
  - Not too much skew (check using histograms as in Session B15)
  - Test can be fooled in some situations

Simple Random Sampling

- Row-level oversampling
  - Ex: 75 sample rows from 10,000 row table

```
WITH dt AS (SELECT * FROM mytable TABLESAMPLE BERNOULLI(1))
SELECT * FROM dt ORDER BY RAND()
FETCH FIRST 75 ROWS ONLY
```

- Page-level oversampling
  - Ex: 75 sample pages from 10,000 page table

```
WITH dt1 AS (SELECT c1,...,cN,SAMPLE_UNIT_ID(c1) AS page_num
             FROM mytable TABLESAMPLE SYSTEM(1)),
     dt2 AS (SELECT DISTINCT page_num FROM dt1),
     dt3 AS (SELECT page_num FROM dt2
             ORDER BY RAND()
             FETCH FIRST 75 ROWS ONLY)
SELECT c1,...,cN
FROM dt1,dt3
WHERE dt1.page_num = dt2.page_num
```

Cluster Sampling

- Ex 1: Transactions for a customer
  - Select random set of customers
  - Include all transactions for each selected customer

```
WITH sampcust AS
 (SELECT cust_id
  FROM customers TABLESAMPLE SYSTEM(5))
SELECT transactions.amount,
       transactions.date
FROM transactions, sampcust
WHERE transactions.custid = sampcust.custid
```

- Ex 2: Previous example with TRANS and TRANSITEM

Stratified Sampling

```
(SELECT name,address,salary,gender
  FROM census TABLESAMPLE BERNOULLI(10)
  WHERE gender = 'M'
  ORDER BY RAND() SELECT FIRST 75 ROWS ONLY)
UNION
(SELECT name,address,salary,gender
 FROM census TABLESAMPLE BERNOULLI(10)
 WHERE gender = 'F'
 ORDER BY RAND() SELECT FIRST 75 ROWS ONLY)
```

Systematic Sampling

- Fix sampling parameter k
- Select row at random from first k rows
- Select every kth row thereafter

```
WITH
  dt1(startval) AS (VALUES(1 + INTEGER(rand() * :k))),
  dt2 AS (SELECT ROWNUMBER() OVER () AS rownum, t.*
         FROM t)
SELECT dt2.*
FROM dt1, dt2
WHERE MOD(dt2.rownum-dt1.startval,:k) = 0
```

Split Samples

- Mark each row in a 2-column table
  - As training (1) or testing (2) or not in sample (0)
- 30% sample, with 1/3 training and 2/3 testing

```
WITH dt AS
 (SELECT c1, c2, RAND(1) AS rno FROM t)
SELECT c1, c2,
  CASE
    WHEN rno <= 0.1 THEN 1
    WHEN (rno > 0.1) AND (rno <= 0.3)
THEN 2
    ELSE 0
  END AS sampleid
FROM dt
```

Approximate Drill-Down

```
SELECT country, state, city, year, month,
  avg(value)as avg_sales,
FROM trans tablesample(:samp_rate), loc
WHERE trans.locid = loc.locid
GROUP BY ROLLUP(country, state, city),
         ROLLUP(year, month)
HAVING count(*) > 100
```

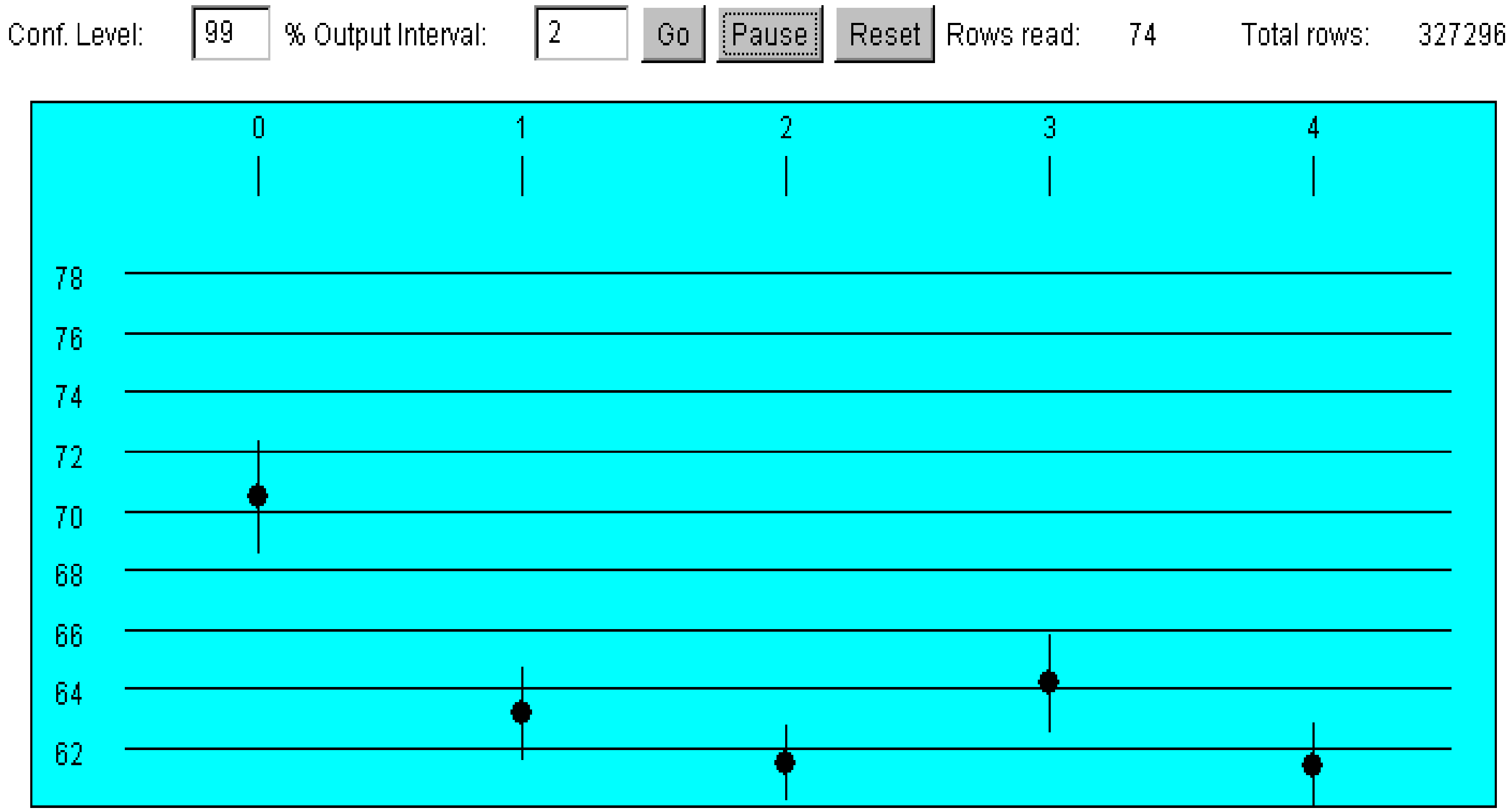
- Drill down by increasing sampling rate
  - low sampling rates => (year), (country), (year, country)
  - high sampling rates => (year, month, country, state, city) etc.

- More natural than usual (non-sampling) OLAP computation
  - Greater drill-down => more work

Continuous Refinement Via Sampling

- A prototype exploratory interface (74 rows processed)

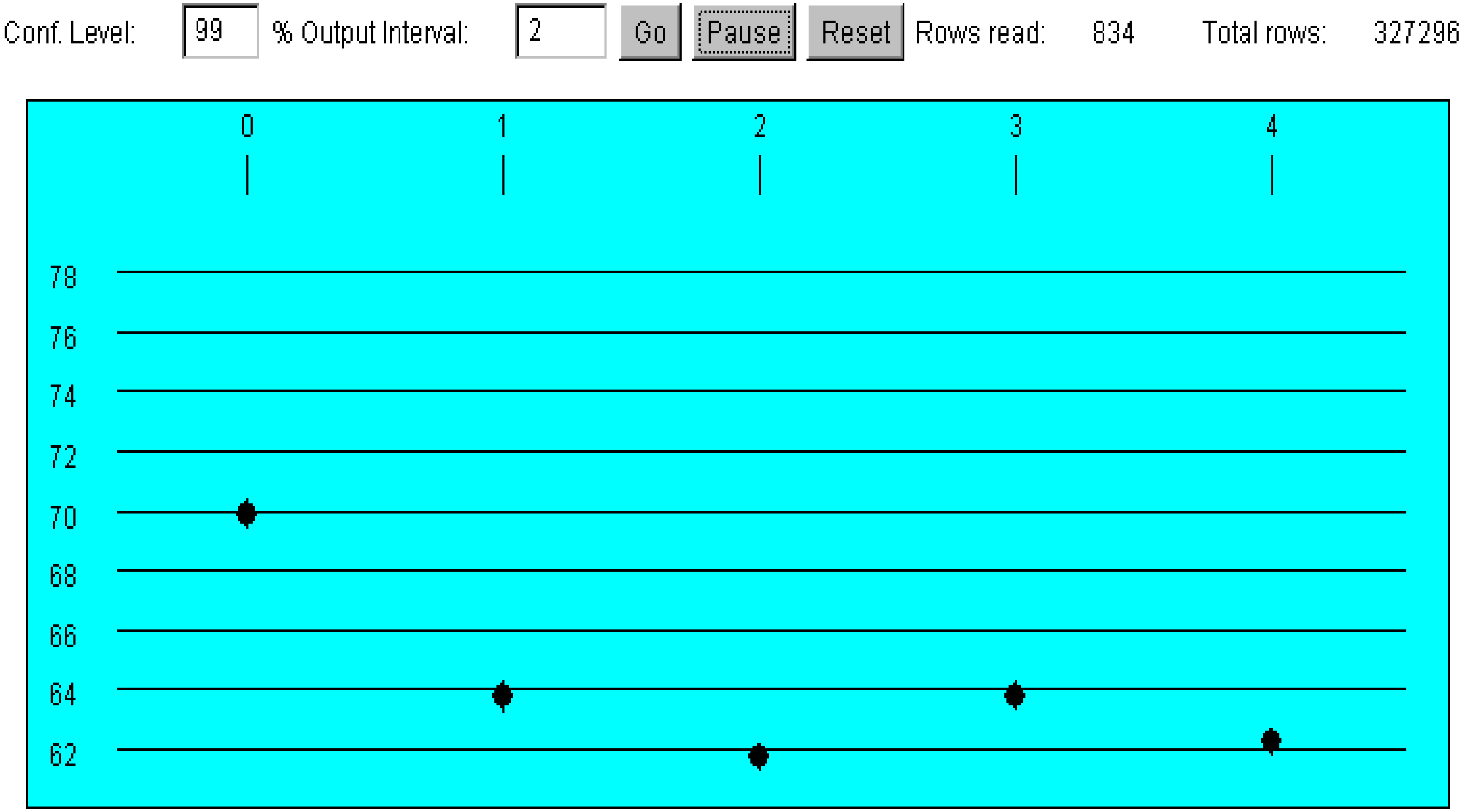
```
SELECT AVG(temp) FROM t GROUP BY site;
```



Conf. Level: 99 % Output Interval: 2 Go Pause Reset Rows read: 74 Total rows: 327296

Continuous Refinement, Continued

- After 834 rows processed:



Conf. Level: 99 % Output Interval: 2

Rows read: 834 Total rows: 327296

Online Technology

- Additional features of online-aggregation interface
  - slowdown/speedup/abort for individual groups
    - i.e., query modification on the fly
    - more resources left for processing other groups
- Lots of new technology
  - new "ripple join" algorithms, online reordering,etc
- Interesting applications
  - online visualization, online spreadsheets
- Collaboration with UC Berkeley (CONTROL project)
  - See references for overviews

Selected References

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Many Thanks To...

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RETURN TO INDEX