EDBT Summer School

Database Performance

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Database Performance: Outline

- Here is an outline of our two-lecture course
- First, we explain why OLTP performance is no longer thought to be an important problem by most researchers and developers
- But we'll introduce a new popular Transactional product called Snapshot Isolation that supports updates & concurrent queries
- Then we look at queries, especially Data Warehouse queries, which get the most performance attention currently
- We explain early query performance concepts, e.g. index Filter Factor, then look at cubical clustering, the new crucial factor
- Data Warehousing is where most new purchases are made at present, and we examine the area in detail

DB Performance: OLTP

- Jim Gray said years ago: OLTP is a solved problem
- Older established companies that do OLTP Order Entry have solutions in place, efficient enough not to need change
- One reason is that change is very difficult: rewriting a company’s OLTP programs is called the “Dusty Decks” problem
  - Nobody remembers how all the code works!
- Also, the cost of hardware to support update transactions compared to programming costs, or even terminal costs, is low
- We explain this in the slides immediately following
- But some new installations use new transactional approaches that better support queries, such as Snapshot Isolation
- We explain Snapshot Isolation a bit later (starting on Slide 7)

OLTP *DebitCredit* Benchmark

- Anon [Jim Gray] et al. paper (in Datamation, 1985) introduced the *DebitCredit* benchmark.

Bank Transaction tables: Acct, Teller, Brnch, History, with 100 byte rows

```
Read 100 bytes from terminal: aid, tid, bid, delta
  Begin Transaction;
     Update Accnt set Accnt_bal = Accnt_bal +:delta where Accnt_ID = :aid;
     Insert to History values (:aid,:tid, :bid, :delta, Time_stamp);
     Update Teller set Teller_bal = Teller_bal + :delta where Teller_ID = :tid;
     Update Brnch set Brnch_bal = Brnch_bal+:delta where Brnch_ID = :bid;
  Commit;
Write 200 bytes to terminal including: aid, tid, bid, delta, Accnt_bal
```

Transactions per second (tps) scaled with size of tables: each tps had 100,000 Accnts, 10 Brnches, 100 Tellers; History held 90 days of inserts

[1] History of DebitCredit/TPC-A in Jim Gray’s “The Benchmark Handbook”, Chapter 2.

OLTP DebitCredit Benchmark

- DebitCredit restrictions; performance features tested
- Terminal request response time required 95% under 1 second; throughput driver had to be titrated to give needed response
- Think time was 100 secs (after response): meant much context had to be held in memory for terminals (10,000 for 100 tps)
- Terminal simulators were used; Variant TP1 benchmark drove transactions by software loop generation with trivial think time
- Mirrored Tx logs required to provide guaranteed recovery
- History Inserts (50 byte rows) costly if pages locked
- System had to be priced, measured in $/tps

OLTP DebitCredit/TPC-A Benchmark

- Vendors cheated when running DebitCredit
- Jim Gray welcomed new Transaction Processing Performance Council (TPC), consortium of vendors, created TPC-A[1] in 1989
- Change from DebitCredit: measurement rules were carefully specified and auditors were required for results to be published
- Detail changes:
  - For each 1 tps, only one Branch instead of 10: meant concurrency would be tougher: important to update Branch LAST
  - Instead of 100 sec Think Time, used 10 sec. Unrealistic, but reason was that TERMINAL PRICES WERE TOO HIGH WITH 100 SEC!

    Terminal prices were more than all other costs for benchmark

    Even in 1989, transactions were cheap to run!

[1] History of DebitCredit/TPC-A in Jim Gray's "The Benchmark Handbook", Chapter 2. In ACM SIGMOD Anthology, http://www.sigmod.org/dblp/db/books/collections/gray93.html

DB Performance: OLTP & Queries

- Amazon doesn’t use OLTP of any DBMS to enter purchases in a customer’s shopping cart (does for dollar transactions though)
- Each purchase is saved using a PC file system, with mirroring & replication for failover in case of node drop-out: log not needed
- Classical OLTP not needed because only one purchase saved at a time on a single-user shopping cart
- There is one new approach to transactional isolation adopted for some new applications, mainly used to support faster queries
- It is called “Snapshot Isolation”[1] (SI), and it has been adopted in both the Oracle and Microsoft SQL Server database products
- SI is not fully Serializable, so it is officially an Isolation Level, but anomalies are rare and Queries aren’t blocked by Update Tx’s

[1] First published in SIGMOD 2005. *A Critique of ANSI Isolation Levels*. by Hal Berenson, Phil Bernstein, Jim Gray, Jim Melton, Pat O’Neil and Elizabeth O’Neil

DB Performance: Snapshot Isolation (SI)

- A transaction T_i executing under Snapshot Isolation (SI) reads only committed data as of the time Start(T_i)
- This doesn't work by taking a "snapshot" of all data when new Tx starts, but by taking a timestamp and keeping old versions of data when new versions are written: Histories in SI read & write "versions" of data items
- Data read, including both row values and indexes, time travels to Start(T_i), so predicates read by T_i also time travel to Start(T_i)
- A transaction T_i in SI also maintains data it has *written* in a local cache, so if it rereads this data, it will read what it wrote
- No T_k concurrent with T_i (overlapping lifetimes) can read what T_i has written (can only read data committed as of Start(T_k))
- If concurrent transactions both update same data item A, then second one trying to commit will abort (First committer wins rule)

DB Performance: Snapshot Isolation (SI)

- SI Histories read and write Versions of data items: (X0, X1, X2); X0 is value before updates, X2 would be written by T_2, X7 by T_7
- Standard Tx'l anomalies of non-SR behavior don't occur in SI
- Lost Update anomaly in Isolation Level READ COMMITTED (READ COMMITTED is Default Isolation Level on all DB products) :

  (I'm underlining T_2's operations just to group them visually)

  H1: $R_1(X,50)$ $\underline{R_2(X,50)\ W_2(X,70)\ C_2}$ $W_1(X,60)$ C_1 (X should be 80)
- In SI, First Committer Wins property prevents this anomaly:

  $H1_{SI}$: $R_1(X0,50)$ $\underline{R_2(X0,50)\ W_2(X2,70)\ C_2}$ $W_1(X1,60)$ A_1
- Inconsistent View anomaly possible in READ COMMITTED:

  H2: $R_1(X,50)$ $\underline{R_2(X,50)\ W_2(X,70)\ R_2(Y,50)\ W_2(Y,30)\ C_2}$ $R_1(Y,30)$ C_1
- Here T1 sees X+Y = 80; In SI, Snapshot Read avoids this anomaly

  $H2_{SI}$: $R_1(X0,50)$ $\underline{R_2(X0,50)\ W_2(X2,70)\ R_2(Y0,50)\ W_2(Y2,30)\ C_2}$
  $R_1(Y0,50)$ C_1 (T_1 reads sum of X+Y = 100, valid at Start(T_1)

DB Performance: Snapshot Isolation

- In SI, READ-ONLY T_1 never has to wait for Update T_2 since T_1 reads consistent committed data at Start(T_1)
- Customers LIKE this property!
- SI was adopted by Oracle to avoid implementing DB2 Key Value Locking that prevents predicate anomalies
- In SI, new row insert by T_2 into predicate read by T_1 won’t be accessed by T_1 (since index entries have versions as well)
- Customers using Oracle asked Microsoft to adopt SI as well, so Readers wouldn’t have to WAIT

DB Performance: Snapshot Isolation

- Oracle calls the SI Isolation Level “SERIALIZABLE”
- SI is not truly SERIALIZABLE (SR); anomalies exist
- Assume husband and wife have bank account balances A and B with starting values 100; Bank allows withdrawals from these accounts to bring balances A or B negative as long as A+B > 0
- This is a weird constraint; banks probably wouldn’t impose it
- In SI can see following history:

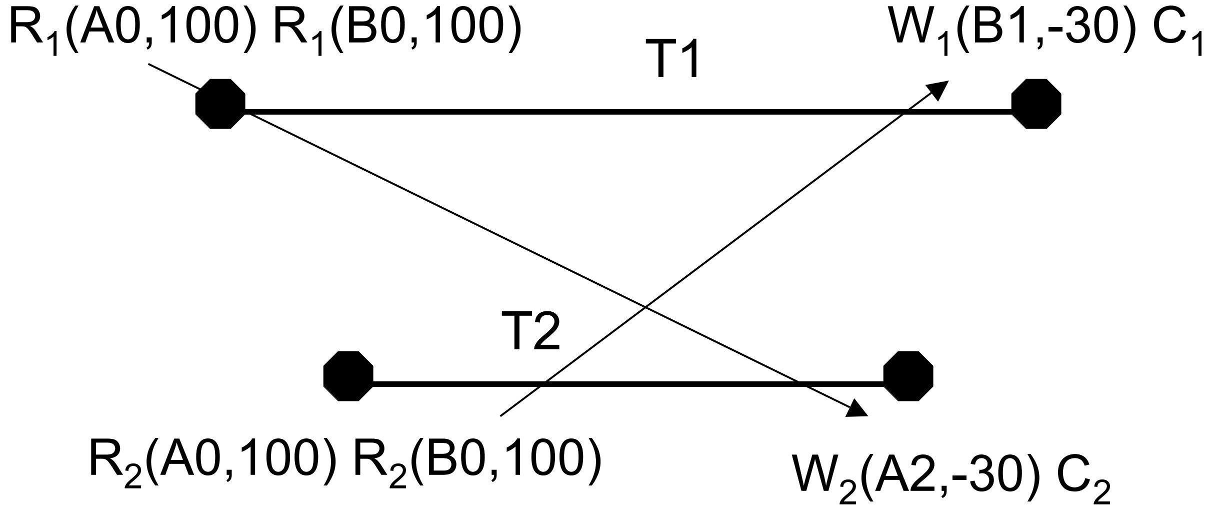
  H3: $R_1(A0,100)$ $R_1(B0,100)$ $\underline{R_2(A0,100)\ R_2(B0,100)\ W_2(A2,-30)\ C_2}$ $W_1(B1,-30)$ C_1

  Both T_1 and T_2 expect total balance will end positive, but it goes negative because each Tx has value it read changed by other Tx

  This is called a “Skew Writes” anomaly: weird constraint fails

Snapshot Isolation Skew-Write Anomaly

$R_1(A0,100)\ R_1(B0,100)\ \underline{R_2(A0,100)\ R_2(B0,100)\ W_2(A2,-30)\ C_2}\ W_1(B1,-30)\ C_1$



Conflict cycle allowed by SI

Time-->

DB Performance: Snapshot Isolation

- Here is a Skew Write anomaly with no pre-existing constraint
- Assume T_1 copies data item X to Y and T_2 copies Y to X
- R_1(X0,10) R_2(Y0,20) W_1(Y1,10) C_1 W_2(X2,20) C_2
- Concurrent T_1 & T_2 only exchange values of X and Y

  But any serial execution of T_1 & T_2 would end with X and Y identical, so this history is not SR
- Once again we see an example of skew writes: each concurrent Tx depends on value that gets changed
- The rule (constraint?) broken is quite odd, and unavoidable: it is one that comes into existence only as a post-condition!

DB Performance: Snapshot Isolation

- SI anomalies rarely occur in commercial applications
- Oracle called SI “SERIALIZABLE” when they learned it had no anomalies in the (Tx’l) TPC-C benchmark
- It is also usually possible to prevent SI anomalies with proper forethought[1]: here is Skew Write anomaly

  $R_1(X0,10)\ R_2(Y0,20)\ W_1(Y1,10)\ C_1\ W_2(X2,20)\ C_2$
- Can “Select For Update” Oracle, like Writing same value so Crucial read is stable (symbolize below with RU)

  $RU_1(X0,10)\ RU_2(Y0,20)\ W_1(Y1,10)\ C_1\ W_2(X2,20)\ A_2$
- SI shows there ***is*** transactional research possible, but ANTS product writeup[1] seems to push OLTP performance to its limit!

[1] For details see: A. Fekete, D. Liarokapis, E. O’Neil, P. O’Neil and D. Shasha. *Making Snapshot Isolation Serializable*. ACM TODS, Vol 30, No. 2, June 2005

[2] Download from http://www.cs.umb.edu/~poneil/ANTS.pdf

DB Performance: Queries

- Companies are spending the most money now on developing query systems, with few, if any, updates
- I'll start with some historical development
- E. F. Codd's Relational Paper was published in 1970; Codd worked at IBM; DB2 was first released in 1982
    - SEQUEL, early SQL, was published[1] in 1974 for use in IBM's System R, a DB2 precursor
    - ORACLE (then Relational Software, Inc.) put out a commercial version of SQL in 1979

[1] Donald Chamberlin and Raymond Boyce, 1974. *SEQUEL: A Structured English Query Language.* SIGFIDET (later SIGMOD), pp. 249-264.

DB Performance: Early DB2 & M204

- DB2 Query Indexes were explained in 1979 paper[1]
- Rather primitive: Choose single column restriction that gives smallest “selectivity factor” F
  - Selectivity factor was later “Filter Factor” in documentation
  - The ability to AND Filter Factors waited until DB2 V2, 1988
- After DB2 was introduced, Pat was working at CCA, which sold a DBMS called Model 204 (M204) with efficient bitmap indexing
- Pat published a paper called “The Set Query Benchmark”[2] that compared M204 query performance to that of DB2 on MVS
- Lucky that DB2 allowed this: DBMS products today would sue

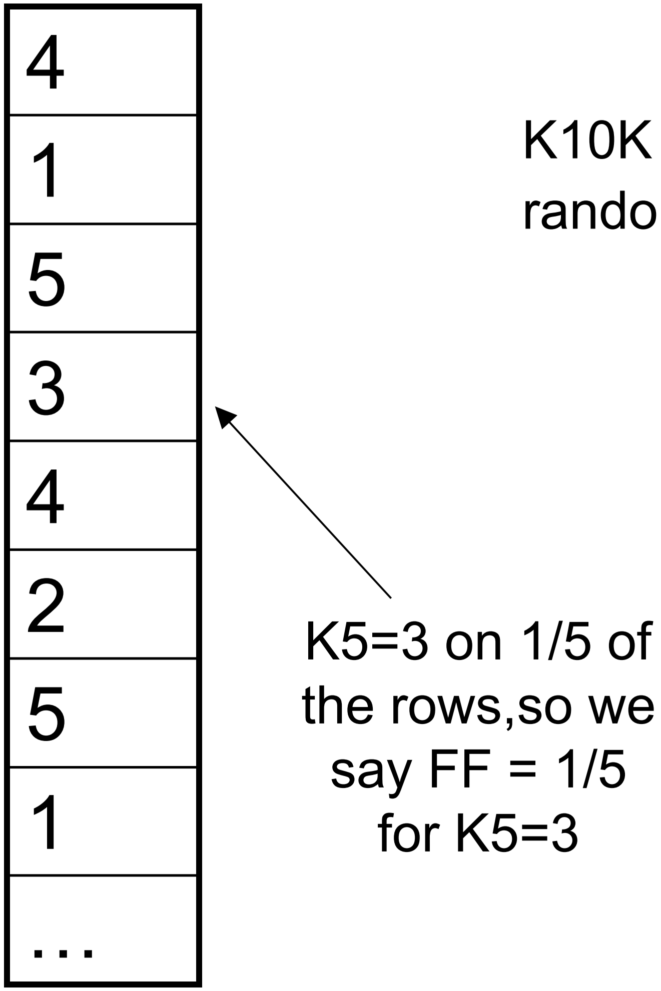
[1] P.G. Selinger et al., *Access Path Selection in a relational database management system*. SIGMOD 1979; [2] P. O'Neil. *The Set Query Benchmark*. Chapter 6 in *The Benchmark Handbook for Database and Transaction Processing Systems*. (1st Edition, 1989, 2nd Ed., 1993)

DB Performance: Set Query Benchmark

- Set Query Benchmark (SQB) has one table: BENCH (we tested table join performance using self-joins on single BENCH table)
- BENCH table has 1,000,000 200-byte rows with a clustering column KSEQ having sequential values 1, 2, . . ., 1,000,000
- Also 12 random-valued columns, names indicating cardinality: K2, K4, K5, K10, K25, K100, K1K, K10K, K100K, K250K, K500K
- E.g.: K10K has 10,000 values, each appearing randomly on about 100 rows & K5 has 5 values, each on about 200,000 rows
- Additionally, 8 char string columns bring row up to 200 bytes
- Finally, we had 9 Query Suites providing “functional coverage” of different forms of decision support in application use
- Each Suite has multiple queries with a range of different Filter Factors (FFs) to provide “selectivity coverage”; SSB can be used as a “micro-benchmark” to predict performance of applications

Set Query Benchmark KNK columns

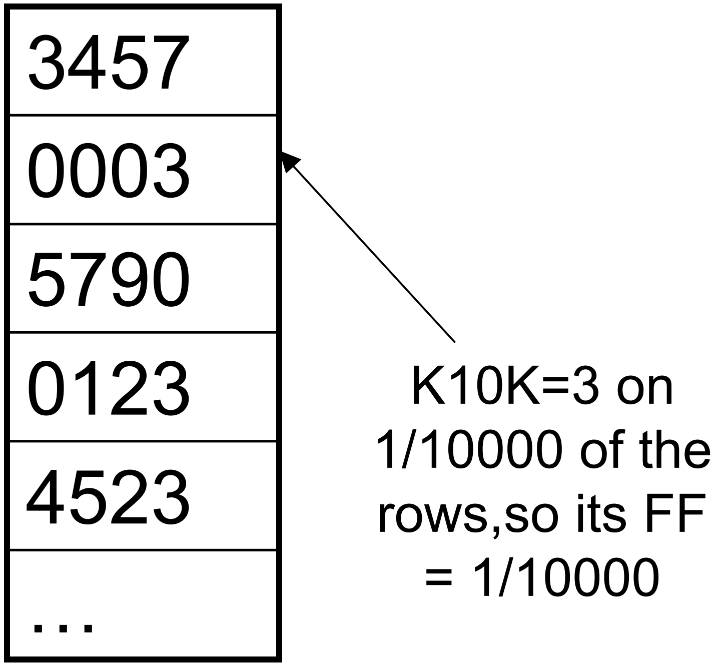
K5 has 5 values, each appearing randomly on about 200,000 rows



4
1
5
3
4
2
5
1
…

K5=3 on 1/5 of the rows,so we say FF = 1/5 for K5=3

K10K has 10,000 values, each appearing randomly on about 100 rows



3457
0003
5790
0123
4523
…

K10K=3 on 1/10000 of the rows,so its FF = 1/10000

DB Performance: Set Query Benchmark

- Here is an example of Query Suite Q3B (underline: fix handout)

```
SELECT SUM(K1K) FROM BENCH
    WHERE (KSEQ between 4000000 and 4100000 OR KSEQ between 4200000 and 4300000
        OR KSEQ between 4400000 and 4500000 OR KSEQ between 4600000 and 4700000
        OR KSEQ between 4800000 and 5000000) AND KN = 3;  -- KN varies from K5 to K100K

----------------------------|==|---|==|---|==|---|==|---|==|==|-----------------------------------------------------
  KSEQ->                   400000                              500000 (midpoint in KSEQ)
```

- This query sums dollar sales of a product of varying popularity sold in a given locale (thus in a broken range of zip codes)
- DB2 and M204 both ran on IBM mainframe system MVS; Note that the FF for KSEQ range is 0.06 and for KN = 3 is 1/CARD(KN)
- DB2 did very well on queries requiring sequential or skip-sequential access to data (called sequential prefetch or list-prefetch by DB2), useful in Q3B
- We wish to contrast performance in 1988-9 measurements of MVS DB2 vs 2007 measurements of DB2 UDB on Windows

DB Performance: Set Query Comparison

- On Windows ran DB2 UDB on a 10,000,000 row BENCH table using very fast modern system (very cheap compared to 1990)
- Query Plans for UDB same as MVS for KN = K100K, K10K & K5, but different for KN = K100, K25 and K10
- Composite FF for N = K10K is 0.06*(1/10,000) = 0.000006, so 6 rows retrieved from MVS's 1M, 62 rows from UDB's 10M

KN Used In Q3B	Rows Read (of 1M)	DB2 MVS 1M Rows Index usage	DB2 UDB 10M Rows Index usage	DB2 MVS 1M Rows Time secs	DB2 UDB 10M Rows Time secs
K100K	1	K100	K100	1.4	0.7
K10K	6	K10K	K10K	2.4	3.1
K100	597	K100, KSEQ	KSEQ	14.9	2.1
K25	2423	K25, KSEQ	KSEQ	20.8	2.4
K10	5959	K10, KSEQ	KSEQ	31.4	2.3
K5	12011	KSEQ	KSEQ	49.1	2.1

Set Query Benchmark KNK index example

K10K has 10,000 values, each appearing on about 100 rows

K10K
3457
0003
5790
0123
4523
…

K10K index : B-tree of entries

(only leaf level shown)

Key	RID
…	…
002	23548901
003	56893467
003	59856230
003	64908876
…	
004	45980456
…	…

100 entries for key = 3

DB Performance: Set Query Comparison

- For both DB2 MVS & DB2 UDB, Query Plan for KN = K100K & K10K is: access rows with KN = 3 & test KSEQ in proper ranges
- DB2 MVS had .0001*(.06)*1,000,000 = 6 rows accessed for K10K; DB2 UDB with 10,000,000 rows, had 62 rows accessed
- In these cases of very low selectivity, index driven access to individual rows is still the best Query Plan

KN Used In Q3B	Rows Read (of 1M)	DB2 MVS Index usage	DB2 UDB Index usage	DB2 MVS Time secs	DB2 UDB Time secs
K100K	1	K100	K100	1.4	0.7
K10K	6	K10K	K10K	2.4	3.1

DB Performance: Set Query Comparison

- For KN = K100, K25 and K10, DB2 MVS ANDED KSEQ and KN = 3 RID-lists, and accessed rows by RID to sum K1K values

```
 xxx xx         x  xxxx x        xx xx x          x xxxx x          xx xx  xxx  x x
|=====|————————|=====|————————|=====| ————————|=====| ————————|==========|
```

- DB2 UDB on the other hand, scans each of five KSEQ ranges specified & tests KN = 3 before summing K1K; DB2 MVS and DB2 UDB ***both*** use that same plan for K5

```
 Scan&Tst        Scan&Tst         Scan&Tst          Scan&Tst            Scan and Test
|=====|————————|=====| ————————|=====| ————————|=====| ————————|==========|
```

KN Used In Q3B	Rows Read (of 1M)	DB2 MVS Index usage	DB2 UDB Index usage	DB2 MVS Time secs	DB2 UDB Time secs
K100	597	K100, KSEQ	KSEQ	14.9	2.1
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K10	5959	K10, KSEQ	KSEQ	31.4	2.3
K5	12011	KSEQ	KSEQ	49.1	2.1

DB Performance: Set Query Comparison

- Both indexed retrieval of individual rows and sequential scan have sped up since DB2 MVS, but sequential scan much more!
- Sequential scan speed has increased from MVS to UDB by a factor of 88; random row retrieval speed by a factor of 4
- FFs for speeding up random row retrieval are less important, but clustering is more important: reduces sequential scan range

KN Used In Q3B	Rows Read (of 1M)	DB2 MVS Index usage	DB2 UDB Index usage	DB2 MVS Time secs	DB2 UDB Time secs
K100K	1	K100	K100	1.4	0.7
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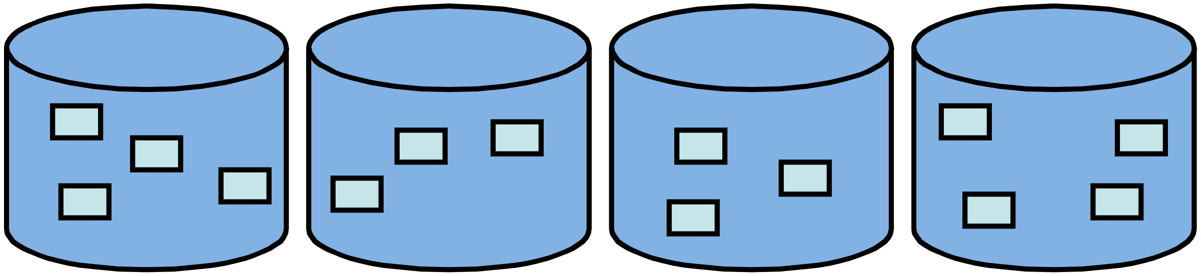
Disk Performance

- Our “disktest” program generates read requests to a 20 GB file, as a database would
  - Sits on 4-disk RAID system of enterprise disks (15K RPM)
  - Various read request sizes: rsize = 4KB, 16KB, 64KB, 256KB
  - From 1 to 300 read requests outstanding
  - Either read whole file in order in rsize reads, or only some of it: “skip-sequential” reads
  - We use random numbers to determine successive rsize blocks to read, with probability p, p = 1.0, 0.1, 0.01, 0.001
- Case of p = 1.0 specifies sequential reading, like a table scan
- Case of p < 1.0 specifies skip-sequential, like index-driven database access: ordered RIDs access rows left-to-right on disk
- DB2 orders RIDs before accessing, ORACLE seems not to

Disk Performance



- Rectangles in disks above represent requests queued in each individual disk of a RAID set with multiple requests outstanding (SCSI or SATA)
- Each disk runs the “elevator” algorithm, modified to handle rotational position, to optimize its work
- For skip-sequential reading, we need 20 requests outstanding for good performance, 5 in each disk
  - This is 3-5 times faster than with 1 request outstanding
  - But not highest MB/s: disk has to rotate between reads
  - Note: stripe size doesn’t matter here, as long as multiple stripes of data are in play

Sequential Scan Performance

- Each disk can deliver 100MB/second with sequential scan
- But throughput from disk to memory is limited by controller/bus
- Disktest, reading sequentially, gets a maximum of 300MB/sec
  - Need reads aligned to stripe boundaries to achieve maximum 300MB/sec
  - Our 4-disk RAID has 64KB stripe size, the Windows page I/O size
  - With 256KB reads (4 disk *stripe set*), only need 2 requests outstanding for 300MB/sec
  - 64KB reads (1 disk stripe at a time), 20 requests outstanding for 300MB/sec
  - Maximum read speed is not attainable with 4KB or 16KB reads
- DBs get about 140 MB/second using tablescan (after tuning)
  - Slowed down by needing to interpret data read in, extract rows, etc.
- Need to tune DBs to use large reads, multiple outstanding reads
- Oracle and Vertica recommend 1MB stripe size for DB RAID

Pointers on Setting up disks for DBs

- When experimenting, should partition RAID into (say) 5 parts
- Then can save tuned databases on different partitions
- Can reinitialize file system on old partition and copy data from another; avoids file system fragmentation of multiple loads
- Can also build a new database on reinitialized partition
- Don’t worry about “raw disk”: current OS file I/O is great
- You will find that the lower-numbered partitions have faster sequential reads, because of disk “zones”
  - effect is about 30% for enterprise disks, more for cheap disks
  - Just be aware of this effect, so you don’t misinterpret results
- You can buy enterprise disks to use on an ordinary tower PC
  - We used a Dell PowerEdge 2900, nice accessible internals
  - Added SAS RAID controller, SAS disks

DB Performance:Outline of What Follows

- First, we'll examine Clustering historically, then a new DB2 concept of Multi-Dimensional Clustering (MDC)
- We show how a form of MDC can be applied to other DBMS products as well, e.g., Oracle, Sybase IQ
- We want to apply this capability in the case of Star Schema Data Warehousing, but there's a problem
- We explain Star Schemas, and how the problem can be addressed by Adjoined Dimension Columns
- We introduce a "Star Schema Benchmark" and show performance comparisons of three products

DB Performance: Linear Clustering

- Indexed clustering is an old idea; in 1980s one company had demographic data on 80 million families from warranty cards

  They crafted mail lists for sales promotions of client companies
- Typically, they concentrated on local areas (store localities) for these companies to announce targeted sales: sports, toys, etc.
- To speed searches, they kept families in order by zipcode; also had other data, so could restrict by incomeclass, hobbies, etc.
- The result was something like like Q3B: a 50 mile radius circle in a state will result in a small union of ranges on zipcode
- The Q3B range union was a fraction 0.06 of all possible values in clustering column KSEQ in BENCH
- Clustered ranges are all the more important with modern disks

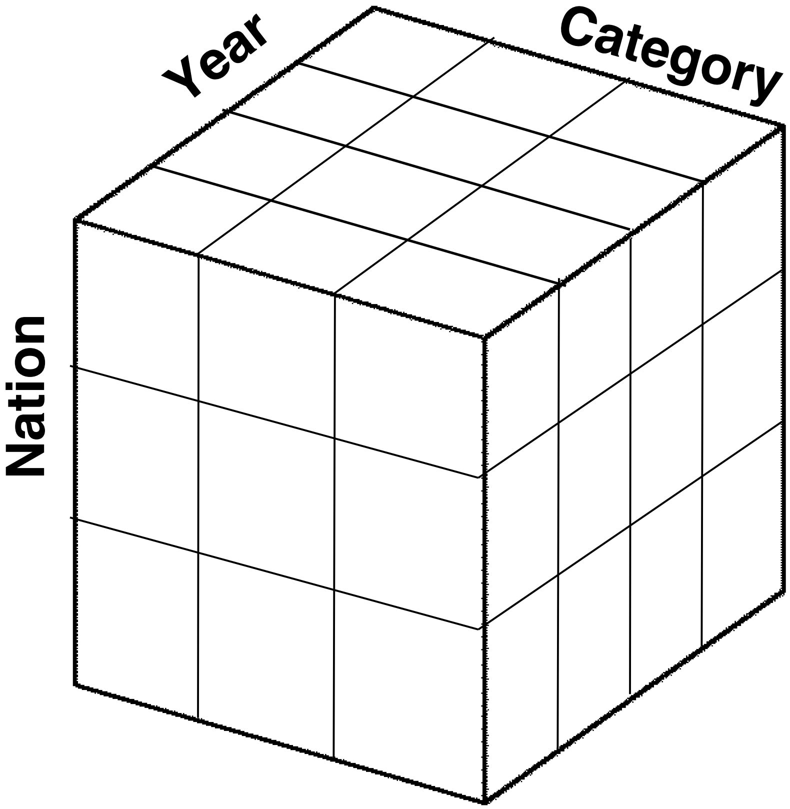
Multi-Dimensional Clustering

- Clustering by a single column of a table is fine if almost all queries restrict by that column, but this is not always true
- DB2 was the first DBMS to provide a means of clustering by more than one column at a time using MDC[1]
- MDC partitions table data into Cells by treating some columns within the table as axes of a Cube
- Each Cell in a Cube is defined by a combination of values in Cube axis columns: Each row's axis values define its Cell
- New rows are placed in its Cell, which sits on a sequence of Blocks on disk; Blocks must be large enough so sequential scan access speed on the cell swamps inter-cell access seek
- Queries with multiple range predicates on axis columns will retrieve only data from Cells in range intersection

[1] S. Lightstone, T. Teory and T. Nadeau. *Physical Database Design*. Morgan Kaufmann

DB Performance: Multi-Dim Clustering

- Example cube on dimensions: Year, Nation, Product Category



DB Performance: Multi-Dim Clustering

- Define DB2 MDC Cells in Create Table statement

```
create table Sales(units int, dollars decimal(9.2), prodid int, category int, nation
char(12), selldate date, year smallint, . . .)
        organize by dimensions (category, nation, year);
```

- Cells on category, nation and year are created, sit on blocks
- Each value of a dimension gives a *Slice* of the multi-dimensional cube; has *Block index* entry listing BIDs of Blocks with that value
- The BIDs in the intersection of all orthogonal Slices is for a *Cell*
- DB2 supports Inserts of new rows of a table in MDC form; new rows are placed in some Block of the valid Cell, with new Block added if necessary; after Deletes, empty Blocks are freed
- No guarantee Blocks for a Cell are near each other, but inter-block time swamped by speed of sequentially access to a block

MDC organization on disk

Example: MDC with three axes (AKA dimensions), nation, year, category, each with values 1, 2, 3, 4.

Let C123 stand for cell with axis values (1,2,3), I.e., nation = 1, year = 2, category = 3

On disk, each block (1 MB say) belongs to a cell.

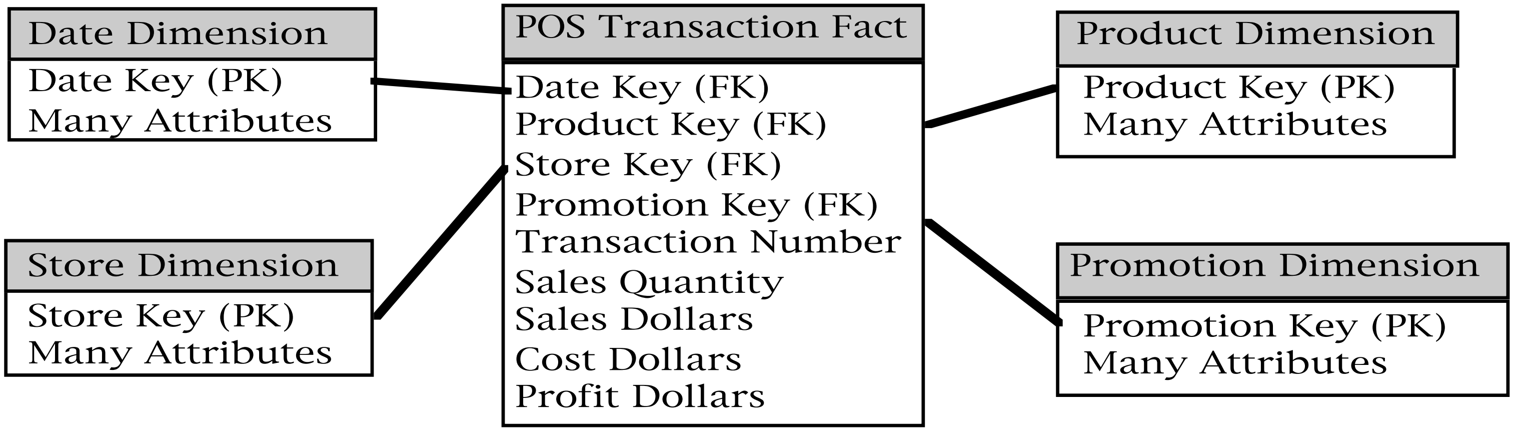
The sequence of blocks on disk is disordered:

C321 C411 C342 C433 C412 C143 C411 C231 C112 …

One cell, say C411, (nation = 4, year = 1, category = 1) has several blocks,in different places, but since each block is 1 MB, it’s worth a seek.

DB Performance: Star Schema (SS)

- A Data Warehouse is a Query-mostly Database, typically made up of multiple Star Schemas, called Data Marts
- Star Schema has Fact table and various Dimension tables



Date Dimension
Date Key (PK)
Many Attributes

Store Dimension
Store Key (PK)
Many Attributes

POS Transaction Fact
Date Key (FK)
Product Key (FK)
Store Key (FK)
Promotion Key (FK)
Transaction Number
Sales Quantity
Sales Dollars
Cost Dollars
Profit Dollars

Product Dimension
Product Key (PK)
Many Attributes

Promotion Dimension
Promotion Key (PK)
Many Attributes

DB Performance: Star Schema (SS)

- In general, Dimension tables have a very small number of rows compared to a Fact table
- POS Transaction Fact Table has 9 columns, 40 byte rows
- Maximum size of a POS table on an inexpensive PC might need a few hundred GB of disk, which would amount to 5 billion rows
- Dimension tables are much smaller: few thousand rows in Date, Store Dimensions, 100s in Promotion, few million in Product
- Practitioners keep Fact tables lean,Foreign Keys, TID and Measures, have many descriptive columns in Dimension Tables

  E.g. Product Dimension might have: ProdKey (artificial key), Product Name, SKU (natural key), Brand_Name, Category (paper product), Department (sporting goods), Package_Type, Package _Size, etc

DB Performance: Data Warehousing

- Data Warehouse is made up of collection of Star Schemas often representing supply chain on conforming dimensions[1]

[1] R. Kimball & M. Ross, The Data Warehouse Toolkit, 2nd Ed., Wiley

	CONFORMING DIMENSIONS								
SUPPLY CHAIN STAR SCHEMAS	Date	Product	Store	Promotion	Warehouse	Vendor	Contract	Shipper	Etc.
Retail Sales	X	X	X	X					
Retail Inventory	X	X	X						
Retail Deliveries	X	X	X						
Warehouse Inventory	X	X			X	X			
Warehouse Deliveries	X	X			X	X			
Purchase Orders	X	X			X	X	X	X	

DB Performance: Star Schema Queries

- Queries on Star Schemas typically retrieve aggregates of Fact table measures (Sales Quantity/Dollars/Cost/Profit)
- The Query Where Clauses typically restrict Dimension Columns: Product Category, Store Region, Month, etc.
- Usually some Group By for Aggregation
- Example Query 2.1 from Star Schema Benchmark (SSB):

```
select sum(lo_revenue), d_year, p_brand1
    from lineorder, date, part, supplier
    where lo_orderdate = d_datekey and lo_partkey = p_partkey
        and lo_suppkey = s_suppkey and p_category = 'MFGR#12'
        and s_region = 'AMERICA'
    group by d_year, p_brand1 order by d_year, p_brand1;
```

DB Performance: Multi-Dim Clustering

- Recall that DB2’s MDC treats table columns as orthogonal axes of a Cube; these columns are called “Dimensions”
- But MDC “Dimensions” are columns in a table turned into a Cube, not columns in Dimension tables of a Star Schema
- Of course we can’t embed all Dimension columns of a Star Schema in the Fact table: would take up too much space for huge number of rows
- How does DB2 MDC handle Star Schemas? Not entirely clear
- For a foreign key of type Date a user can define a “generated column” YearAndMonth mapped from Date by DB2; this column’s values can then be used to define MDC Cells
- But not all Dimension columns can have generated columns defined on foreign keys: Product foreign key will not give brand

Adjoined Dimension Columns (ADC)

- To use columns of Star Schema Dimension tables in MDC as Cube Axes we adjoin copies of Dimension columns to Fact table
- We call this “ADC”: Adjoined Dimension Columns for Cube Axes
- Only 3-5 columns adjoined of relatively low cardinality, since the number of Cells is the product of table Axis column values
- Why is low cardinality important?

  Each Cell (or Block of a Cell) must sit on a MB of disk or more, so sequential access in Cell swamps seek time between Cells

  (DB2 MDC documents don’t describe this, but that’s the idea)
- The ADC approach generalizes to DBMS without MDC if we sort Fact table by concatenation of adjoined columns
- We explain all this and measure performance in what follows

ADC: Outline of What Follows

- ADC works well with DB2 MDC or Oracle partitions or even a DBMS that simply has good indexing
- ADC can have problems with inserts to the base table if Cells are not defined on a Materialized View
- We will measure performance using a Star Schema benchmark (SSB): The SSB schema is defined as a transformation of a TPC-H benchmark schema
- We analyze SSB Queries by clustering performed: Cluster Factor (CF) instead of Filter Factor (FF)
- Then we provide experimental results, further analysis, and conclusions

Adjoining Dimension Columns: Example

- Consider adjoining the following dimension columns to the POS Transaction Fact table (Slide pg 27) to give POS^{ADC}
  - Date.Qtr in a 3 year history of transactions, 12 values, as POS.D_Qtr
  - Store.Nation in multi-national sales with 9 nations, as POS.S_Nation
  - Product.Dept, with 18 Departments in the business, POS.P_Dept
  - Promotion.MediaType, with 9 such types, as POS.PR_Type
- Number of cells added to make POS^{ADC} is: 12*9*18*9 = 17,496
- May see skew in count of rows in cell combinations of dimension column values: say smallest cells size is 1/2 size of largest
- We want each cell to contain at least 1 MB so sequential scan swamps seek time between cells: We should be safe assuming 35000 cells of equal size: implies we need 70 GB in POS^{ADC}

Adjoining Dimension Columns

- Note that POS^{ADC} is not a materialized view of POS in all database system products; there will be two separate tables
- Given a row for insert in POS, we use foreign keys in the row to determine ADC column values for insert in POS^{ADC}
- Thus we give up on working with POS to deal with POS^{ADC} unless we always insert new rows in both POS and POS^{ADC}
- Vertica[1] DBMS supports ordered materialized views created from joins of tables: we'll see why ordering can be important shortly

[1] C-Store, A Column-Oriented DBMS, M. Stonebraker et al. http://db.csail.mit.edu/projects/cstore/vldb.pdf

Considerations and Futures of ADC

- If POS^{ADC} is not a materialized view, updates don't keep POS up to date: may be OK if it's only POS^{ADC} we want to work with
- POS^{ADC} isn't much fatter than POS, four extra columns with small cardinality: can make these columns tiny with good compression
- E.g., character string values can EACH be mapped to small ints 1-12; this approach was used in M204: "Coding" compression
- POS^{ADC} Inserts might be slow if must look up ADC in Dimensions
- But it seems possible to encode column values of a dimension hierarchy in a hierarchical foreign key: Region (4 values), Nation (up to 25 per region), City (up to 25 per Nation): 2 + 5 + 5 bits.
- An added advantage is that the DBMS becomes hierarchy aware with just a foreign key: can recognize that an equal match on City implies equal match on containing Country and Region
- This obviates the needs to put "hints" in query of Country/Region

Compressing ADC

- Won’t have all tricks of prior slide in any current DBMS
- But we can usually compress adjoined dimension columns to small ints: use UDF for mapping so Store.Nation = ‘United States’ maps to small int 7

```
create function NATcode (nat char(18)) returns small int
…
return case nat
    when ‘United Kingdom’ then 1
    …
    when ‘United States’ then 7
    …
end
```

- Now a user can write:

  Select … from POS where S_Nation = Natcode(‘United States’)…
- Natcode will translate ‘United States’ to the int 7; thus all ADC can be two-byte (or less) small ints with proper UDFs defined

Using ADC With Oracle

- Oracle has a feature “Partitioning” that corresponds to DB2 MDC
- Given ADCs C1, C2, C3 and C4, create Cells of a Cube using the Partition clause in Create Table on a concatenation of these columns (assume values for columns are 0, 1 & 2, for illustration)

```
…
partition C0001 values less than (0,0,0,1) tablespace TS1
partition C0002 values less than (0,0,0,2) tablespace TS1
partition C0010 values less than (0,0,1,0) tablespace TS1 -- (0,0,1,0) next after (0,0,0,2)
…
partition C1000 values less than (1,0,0,0) tablespace TS2
…                          -- NOTE: Inserts of new rows also work with partitioning
```

- Map Dimension value to number, Oracle compresses to byte if fits

```
create or replace function natcode (nat char(18)) return number is
begin
  return case nat
      when ‘United Kingdom’ then 1
      …
```

Create Cells Using Table Order & ADC

- For DBMS with good indexing, define Cells by concatenating (4) Adjoined Dimension Columns and sorting table by this order
- Each cell represents unique combination of ADC values (2,7,4,3)
- A Where clause with ANDed range predicates on four ADCs, each range over 3 ADC values, will select 81 cells on the table
- Cells Selected will not sit close to each other, except for cells differing only in the final ADC values, e.g.: (2,7,4,3) and (2,7,4,4)
- Obviously this approach doesn't allow later inserts into given cells
- The Vertica DBMS uses this approach, but since new inserts go into WOS in memory, later merged out to disk ROS, new ad hoc inserts ARE possible

Star Schema Benchmark (SSB)

- Recall: Kimball defines a Data Warehouse made up Data Marts represented by Star Schemas on conforming dimensions (pg 27)
- To measure query performance on a Star Schema Data Mart with and without ADC, we define the Star Schema Benchmark (SSB)[1]
- The SSB design is based on that of the TPC-H benchmark[2], used by many vendors to claim superior Data Warehouse performance
- "[TPC-H] is cleverly constructed to avoid using a Snowflake [Star] Schema; [two dozen CIOs have] never seen a data warehouse that did not use a Snowflake schema"[3]
- We base SSB on TPC-H for data warehouse needs; Note TPC has been trying for years to develop a Star Schema benchmark

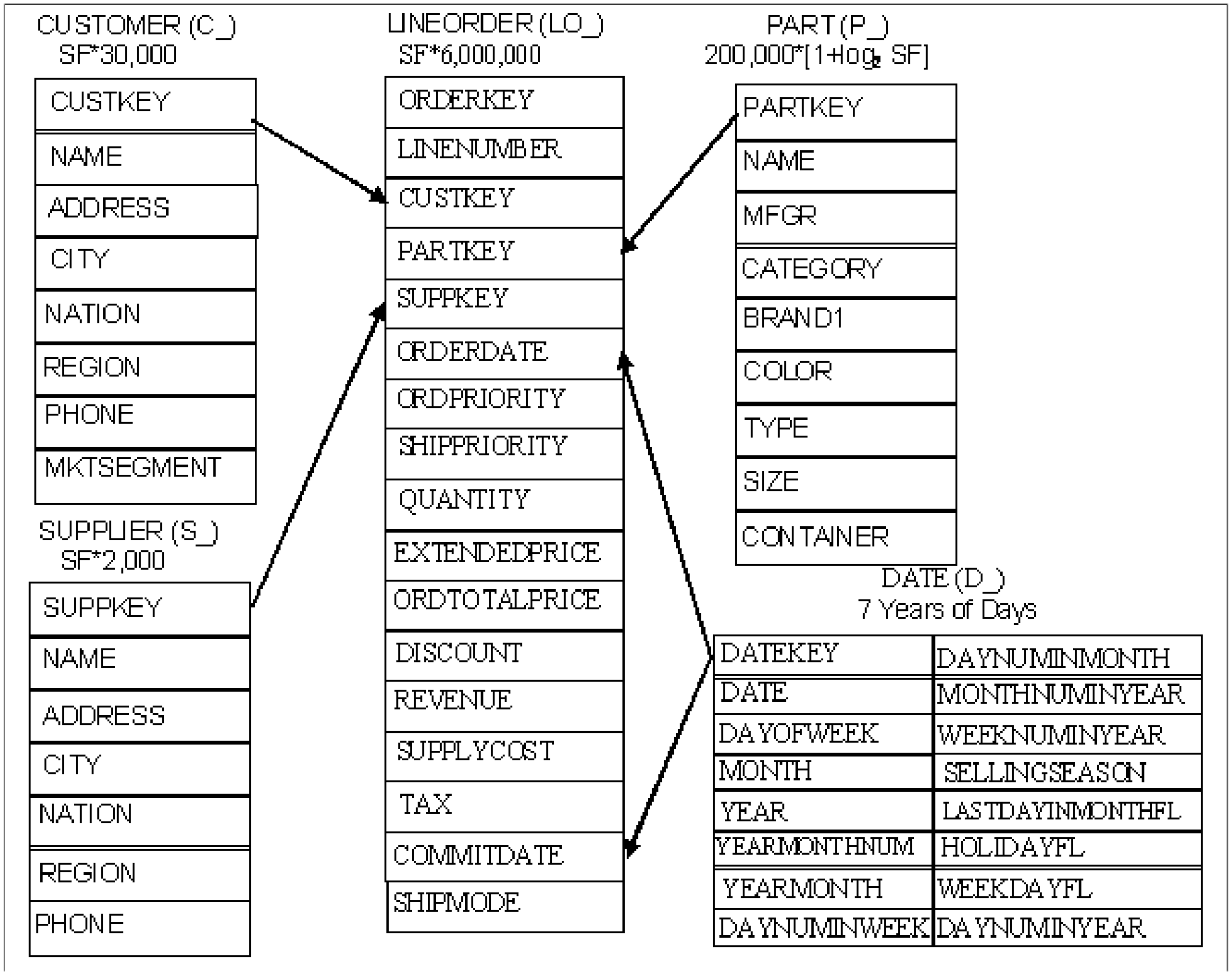
[1] P. O'Neil, E. O'Neil, X. Chen. The Star Schema Benchmark. http://www.cs.umb.edu/~poneil/StarSchemaB.PDF

[2] TPC-H, an ad-hoc decision support benchmark. http://www.tpc.org/tpch/

[3] M. Stonebraker et al., One Size Fits All? — Part 2: Benchmarking Results. http://www-db.cs.wisc.edu/cidr/cidr2007/index.html, press 'Electronic Proceedings' to download

Star Schema Benchmark (SSB)

Created to Measure Star Schema Query Performance



CUSTOMER (C_)
SF*30,000

- CUSTKEY
- NAME
- ADDRESS
- CITY
- NATION
- REGION
- PHONE
- MKTSEGMENT

SUPPLIER (S_)
SF*2,000

- SUPPKEY
- NAME
- ADDRESS
- CITY
- NATION
- REGION
- PHONE

LINEORDER (LO_)
SF*6,000,000

- ORDERKEY
- LINENUMBER
- CUSTKEY
- PARTKEY
- SUPPKEY
- ORDERDATE
- ORDPRIORITY
- SHIPPRIORITY
- QUANTITY
- EXTENDEDPRICE
- ORDTOTALPRICE
- DISCOUNT
- REVENUE
- SUPPLYCOST
- TAX
- COMMITDATE
- SHIPMODE

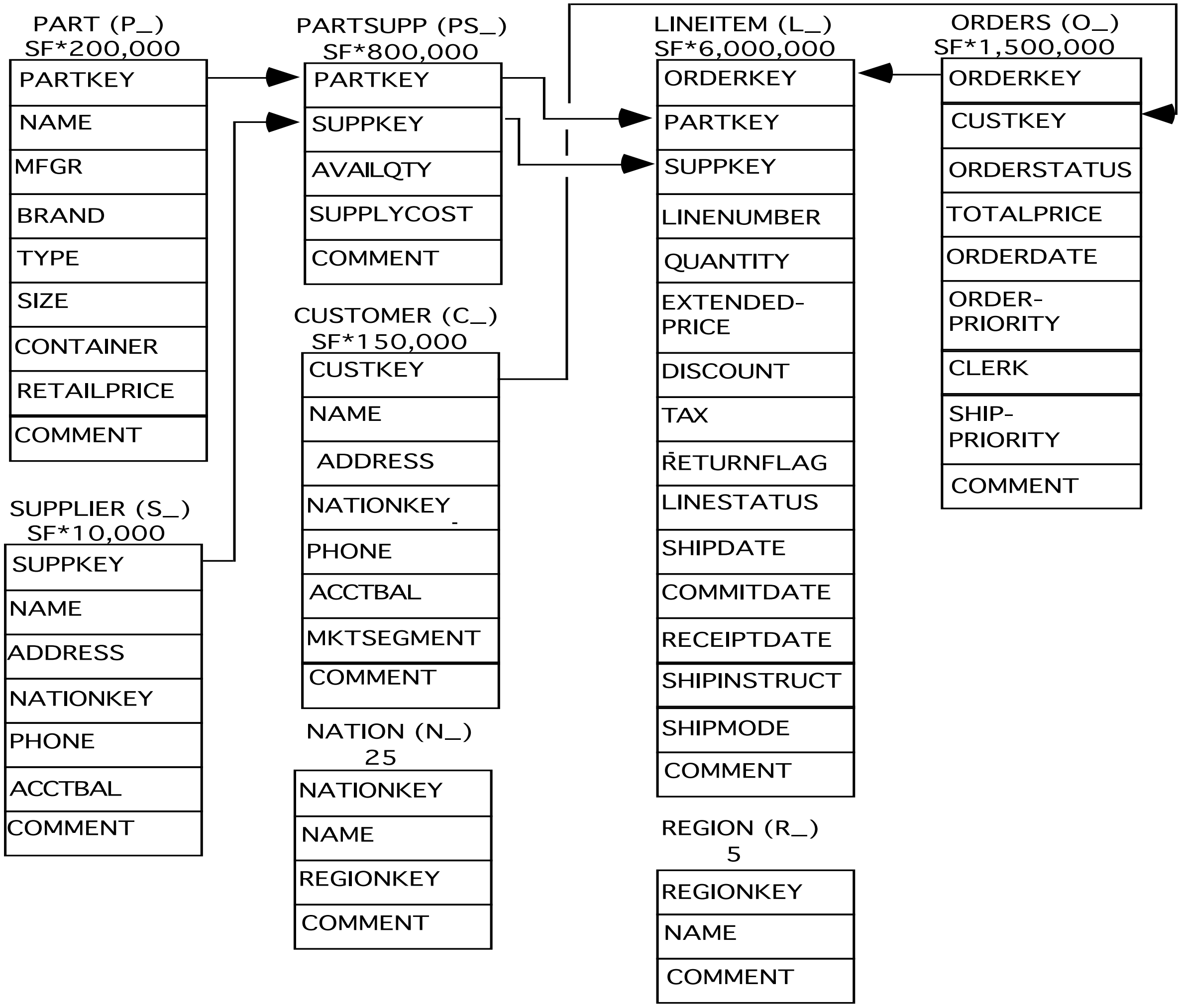
PART (P_)
200,000*[1+log$_2$ SF]

- PARTKEY
- NAME
- MFGR
- CATEGORY
- BRAND1
- COLOR
- TYPE
- SIZE
- CONTAINER

DATE (D_)
7 Years of Days

DATEKEY	DAYNUMINMONTH
DATE	MONTHNUMINYEAR
DAYOFWEEK	WEEKNUMINYEAR
MONTH	SELLINGSEASON
YEAR	LASTDAYINMONTHFL
YEARMONTHNUM	HOLIDAYFL
YEARMONTH	WEEKDAYFL
DAYNUMINWEEK	DAYNUMINYEAR

SSB is Derived From TPC-H Benchmark



PART (P_)
SF*200,000
PARTKEY
NAME
MFGR
BRAND
TYPE
SIZE
CONTAINER
RETAILPRICE
COMMENT

PARTSUPP (PS_)
SF*800,000
PARTKEY
SUPPKEY
AVAILQTY
SUPPLYCOST
COMMENT

LINEITEM (L_)
SF*6,000,000
ORDERKEY
PARTKEY
SUPPKEY
LINENUMBER
QUANTITY
EXTENDED-
PRICE
DISCOUNT
TAX
RETURNFLAG
LINESTATUS
SHIPDATE
COMMITDATE
RECEIPTDATE
SHIPINSTRUCT
SHIPMODE
COMMENT

ORDERS (O_)
SF*1,500,000
ORDERKEY
CUSTKEY
ORDERSTATUS
TOTALPRICE
ORDERDATE
ORDER-
PRIORITY
CLERK
SHIP-
PRIORITY
COMMENT

CUSTOMER (C_)
SF*150,000
CUSTKEY
NAME
ADDRESS
NATIONKEY
PHONE
ACCTBAL
MKTSEGMENT
COMMENT

SUPPLIER (S_)
SF*10,000
SUPPKEY
NAME
ADDRESS
NATIONKEY
PHONE
ACCTBAL
COMMENT

NATION (N_)
25
NATIONKEY
NAME
REGIONKEY
COMMENT

REGION (R_)
5
REGIONKEY
NAME
COMMENT

Why Changes to TPC-H Make Sense

- TPC-H has PARTSUPP table listing Suppliers of ordered Parts to provide information on SUPPLYCOST and AVAILQTY
- This is silly: there are seven years of orders (broken into ORDERS and LINEITEM table) and SUPPLYCOST not stable for that period
- PARTSUPP looks like OLTP, not a Query table: as I fill orders I would want to know AVAILQTY, but meaningless over 7 years?
- AVAILQTY and SUPPLYCOST are never Refressed in TPC-H either; We say PARTSUPP has the wrong temporal "granularity"[1]
- One suspects the real reason for PARTSUPP is to break up what would be a Star Schema, so Query Plans become harder

  Combining LINEITEM and ORDER in TPC-H to get LINEORDER in SSB, with one row for each one in LINEITEM, is common practice[1]

[1] The Data Warehouse Toolkit, 2nd Ed, Ralph Kimball and Margy Ross. Wiley

Why Changes to TPC-H Make Sense

- To take the place of PARTSUPP, we have a column SUPPLYCOST in LINEORDER of SSB to give cost of each item when ordered
- Note that a part order might be broken into two or more lineitems of the order if lowest cost supplier didn't have enough parts
- Another modification of TPC-H for SSB was that TPC-H columns SHIPDATE, RECEIPTDATE and RETURNFLAG were all dropped

  This information isn't known until long after the order is placed; we kept ORDERDATE and COMMITDATE (the commit date is a commitment made at order time as to when shipment will occur)

  One would typically need multiple star schemas to contain other dates from TPC-H, and we didn't want SSB that complicated
- A number of other modifications were made; for a complete list, see: http://www.cs.umb.edu/~poneil/StarSchemaB.PDF

Star Schema Benchmark Queries

- SSB has 13 queries of TPC-H form, with varying numbers of dimension columns restricted & varying selectivity of restrictions; examples follow

Q1.1: Select the total discount given in 1993 for parts sold in quantity < 25 and with discounts of 1-3%

```
select sum(lo_extendedprice*lo_discount) as revenue
    from lineorder, date
    where lo_orderdate = d_datekey and d_year = 1993
        and lo_discount between1 and 3 and lo_quantity < 25;
```

Q2.1: Measure total revenue for a given part category from a supplier in a certain geographical area

```
select sum(lo_revenue), d_year, p_brand1
    from lineorder, date, part, supplier
    where lo_orderdate = d_datekey and lo_partkey = p_partkey and lo_suppkey
        = s_suppkey and p_category = 'MFGR#12’ and s_region = 'AMERICA'
    group by d_year, p_brand1 order by d_year, p_brand1;
```

Star Schema Benchmark Queries

- Successive Queries in a flight (Q1.2, Q1.3 in flight Q1) use tighter restrictions to reduce Where clause selectivity

Q1.1: Select the total discount given in 1993 for parts sold in quantity < 25 and with discounts of 1-3%

```
select sum(lo_extendedprice*lo_discount) as revenue
    from lineorder, date
    where lo_orderdate = d_datekey and d_year = 1993
        and lo_discount between1 and 3 and lo_quantity < 25;
```

Q1.3: Same as Q1.1, except parts sold in smaller range and date limited to one week

```
select sum(lo_extendedprice*lo_discount) as revenue
    from lineorder, date
    where lo_orderdate = d_datekey and d_weeknuminyear = 6 and d. year = 1994
        and lo_discount between 5 and 7 and lo_quantity between 25 and 35
```

- See list of queries starting on page 9 of ADC Index preprint handout

Star Schema Benchmark Cluster Factors

Query	**CF on lineorder**	**CFs of indexable predicates on dimension columns**				**Combined CF Effect on lineorder**
	CF on discount & quantity	CF on Date	CF on part Brand1 roll-up	CF on supplier city roll-up	CF on customer city roll-up	
Q1.1	.47*3/11	1/7				.019
Q1.2	.2*3/11	1/84				.00065
Q1.3	.1*3/11	1/364				.000075
Q2.1			1/25	1/5		1/125 = .0080
Q2.2			1/125	1/5		1/625 = .0016
Q2.3			1/1000	1/5		1/5000 = .00020
Q3.1		6/7		1/5	1/5	6/175 = .034
Q3.2		6/7		1/25	1/25	6/4375 = .0014
Q3.3		6/7		1/125	1/125	6/109375 =.000055
Q3.4		1/84		1/125	1/125	1/1312500= .000000762
Q4.1			2/5	1/5	1/5	2/125 = .016
Q4.2		2/7	2/5	1/5	1/5	4/875 = .0046
Q4.3		2/7	1/25	1/25	1/5	2/21875 = .000091

SSB Test Specifications

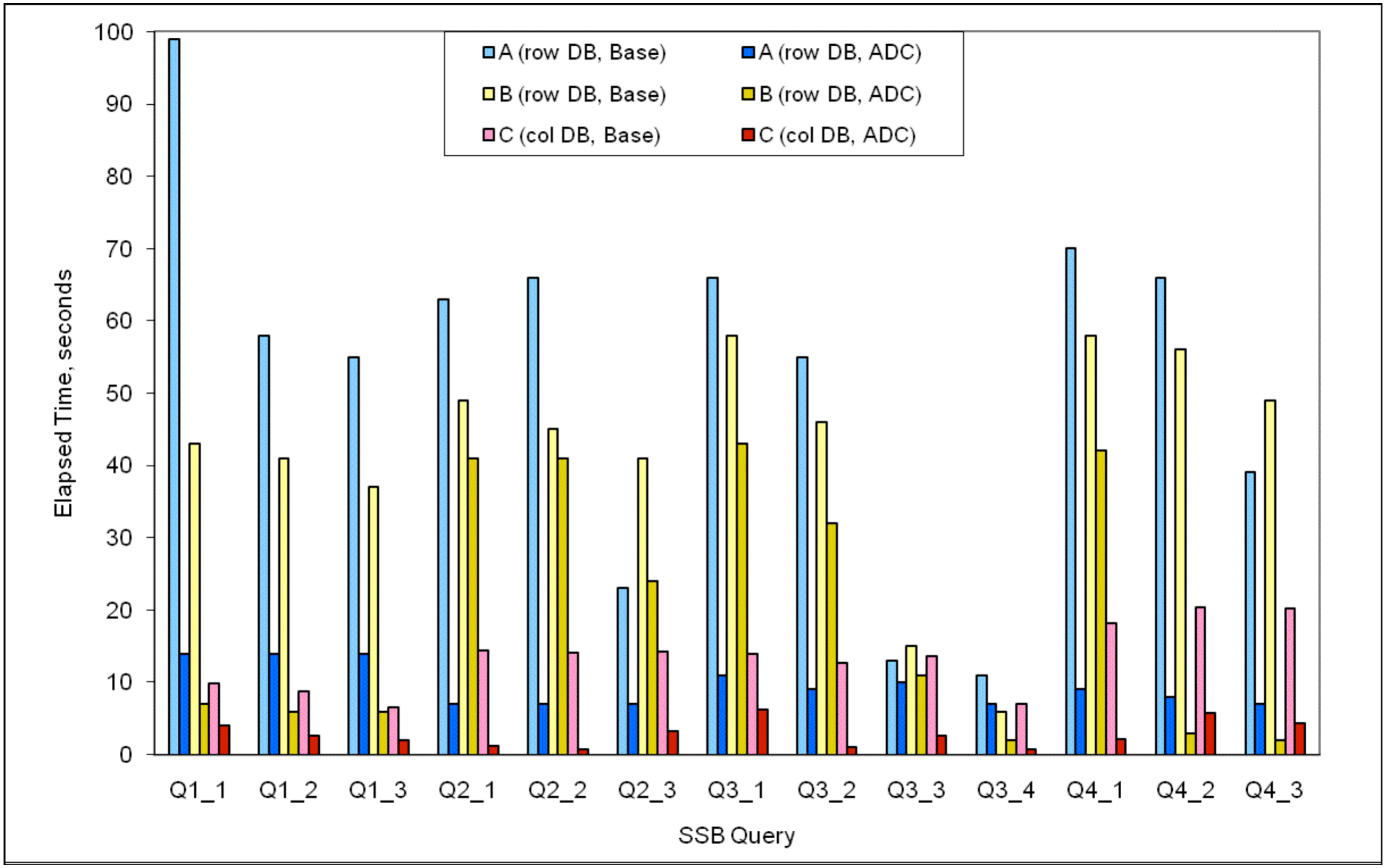
- We measured three DB products we call A, B, and C, using SSB tables at Scale Factor 10, where LINEORDER has about 6 GB
- Tests were performed on a Dell 2900 running Windows Server 2003, with 8 GB of RAM (all queries had cold starts), two 64-bit dual core processors (3.2 GHz each), and data loaded on RAID0 with 4 Seagate 15000 RPM SAS disks (136 GB each), with stripe size 64 KB This is a fast system in current terms;
- We had to experiment to find good tuning settings for number of reads outstanding: parallel threads, prefetching
- Adjoined dimension columns were d.year, s.region, c.region, and p.category (brand-hierarchy), cardinalities 7, 5, 5, and 25
- In LINEORDER table these adjoined columns were named year, sregion, cregion, category, and used in the SSB Queries

SSB Load

- We performed two loads for DBs A, B and C, one with adjoined columns and one with no adjoined columns, called BASIC form
- First we generated rows of SSB LINEORDER and dimensions using generator that populates TPC-H, with needed modifications
- After loading LINEORDER in Basic form, used a query (below) to output the data with adjoined columns in order by concatenation; could use this order to load DB with indexing, or to help speed up DB2 MDC load and Oracle Partition load

```
select L.*, d_year, s_region, c_region, p_category
   from lineorder, customer, supplier, part, date
   where lo_custkey = c_custkey and lo_suppkey = s_suppkey
      and lo_partkey = p_partkey and lo_datekey = d_datekey
   order by d_year, s_region, c_region, p_category;
```

DB Products A, B & C Times in Seconds



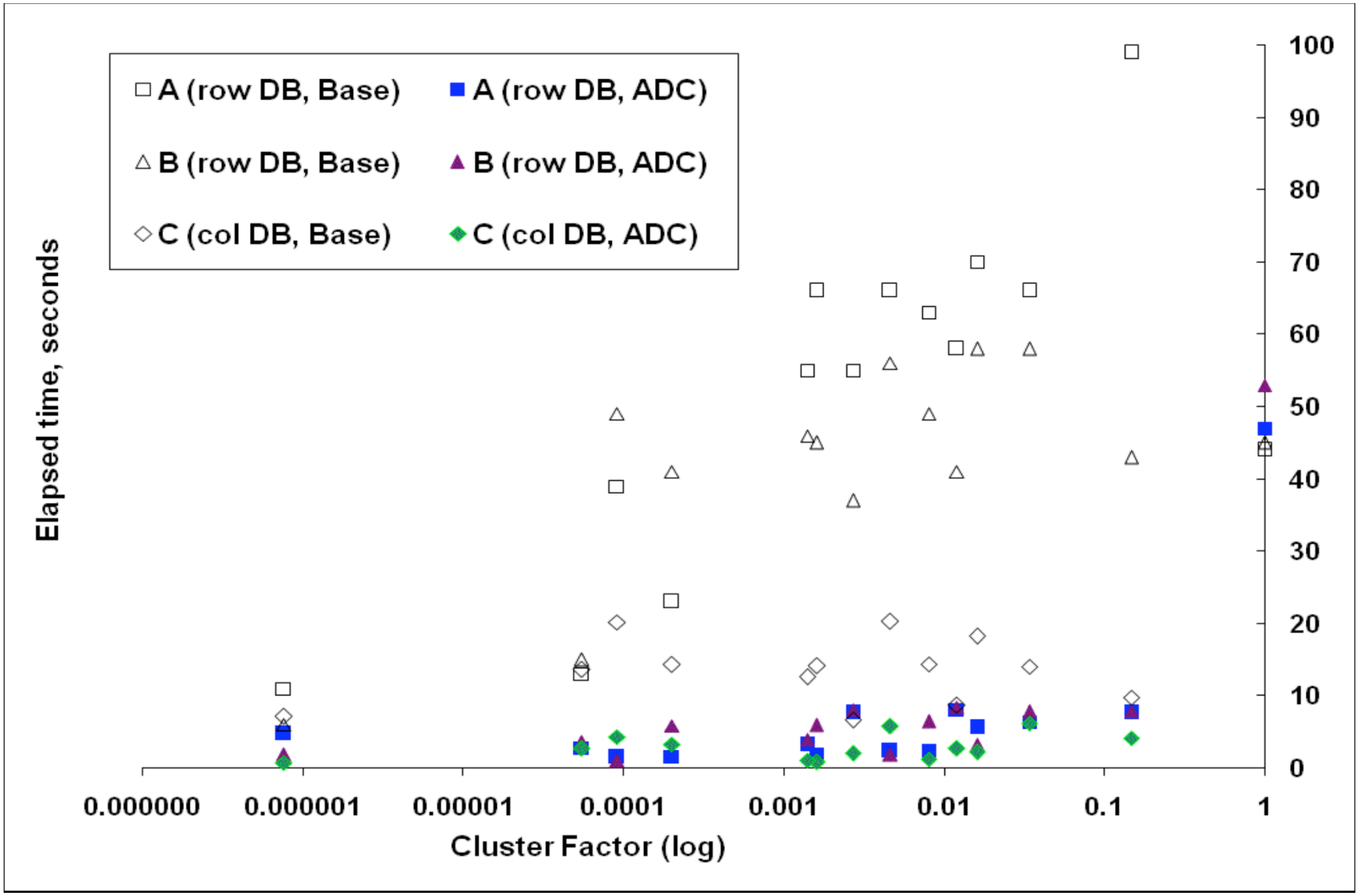
A, B & C Geom. Mean of ADC Measures

- It’s clear that the queries of SSB are best optimized by a column store (also referred to as “vertically partitioned”), DB Product C
- Normal way to summarize N time measures is a geometric mean (used by TPC) : Nth root (Product of N measures)
- The assumption is that faster queries (smaller times) will be used more often, so all queries will have equal weight
- Here are Geometric Means of elapsed & CPU times for A,B,C

	Product A (row DB) Base Case	Product B (row DB) Base Case	Product C (Col, DB) Base Case	Product A (row DB) ADC Case	Product B (row DB) ADC Case	Product C (Col, DB) ADC Case
Geometric Mean of Elapsed/CPU Seconds	44.7/3.4	36.8/1.5	12.6/1.6	3.60/0.24	4.23/0.236	2.29/0.0081

Analysis of SSB and Conclusions

Query Times vs. Cluster Factor, CF (on log scale)



Analysis of SSB and Conclusions

- On plot of slide 56, differentiate three regions of cluster factor: CF
- At low end of the CF Axis (CF < 1/10000), secondary indexes are effective at retrieving few rows qualified: ADC has little advantage
- For CF up near 1.0, the whole table is read with sequential scan regardless of ADC, and the times again group together
- For CF in the intermediate range where most queries lie, ADC reduces query times very effectively compared to the BASE case

  Time is reduced from approximately that required for a sequential scan down to a few seconds (at most ten seconds)
- We believe this demonstrates the validity of our ADC approach

Analysis and Conclusions

- Readers should bear in mind that the Star Schema Benchmark has quite small dimensions, with rather simple rollup hierarchies
- With more complex dimensions and query workloads in large commercial applications, no single ADC choice will speed up all possible queries
- Of course this has always been the case with clustering solutions: they never improve performance of all possible queries
- Still, there are many commercial data warehouse applications where clustering of this sort should be an invaluable aid

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M. Stonebraker et al., One Size Fits All? — Part 2: Benchmarking Results. CIDR 2007 http://www-cs.wisc.edu/cidr/cidr2007/index.html, press 'Electronic Proceedings' to download

TPC-H, an ad-hoc decision support benchmark. http://www.tpc.org/tpch/