02: Data Storage

Andrew Crotty // CS497 // Fall 2023

Observation

Today's lecture is about the lowest physical representation of data in a DBMS.

What data "looks" like determines almost the entire system architecture of a DBMS.

- → Processing Model
- → Tuple Materialization Strategy
- → Operator Algorithms
- → Data Ingestion / Updates
- → Concurrency Control (we will ignore this)
- → Query Optimization

Today's Agenda

Storage Models
Type Representation
Partitioning

Storage Models

A DBMS's <u>storage model</u> specifies how it physically organizes tuples on disk and in memory.

Choice #1: N-ary Storage Model (NSM)

Choice #2: Decomposition Storage Model (DSM)

Choice #3: Hybrid Storage Model (PAX)

N-ary Storage Model (NSM)

The DBMS stores (almost) all attributes for a single tuple contiguously in a page.

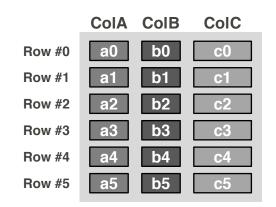
Ideal for insert-heavy and OLTP workloads, where txns tend to access individual entities.

→ Use the tuple-at-a-time *iterator processing model*.

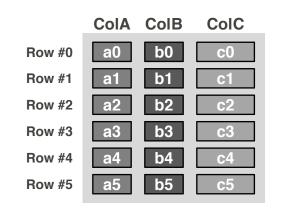
NSM DBMS page sizes are typically some constant multiple of **4 KB** hardware pages.

→ Examples: Oracle (4 KB), Postgres (8 KB), MySQL (16 KB)

A disk-based NSM DBMS stores a tuple's fixed-length and variable-length attributes contiguously in a single slotted page.

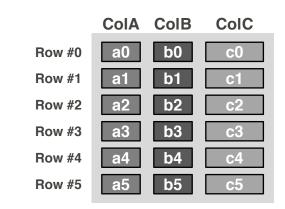


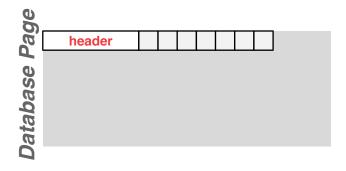
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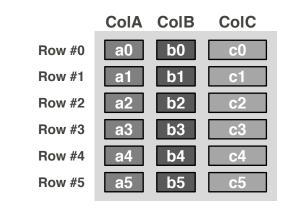


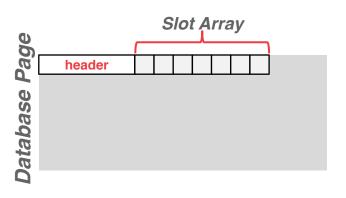
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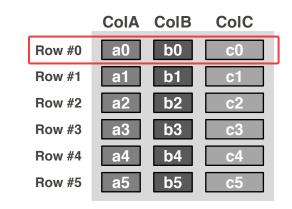


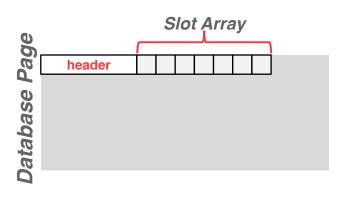
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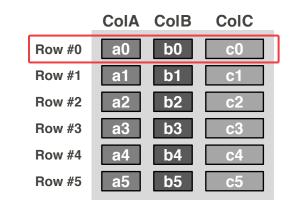


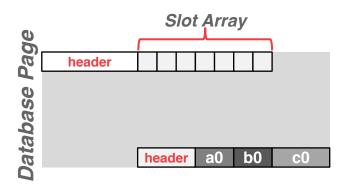
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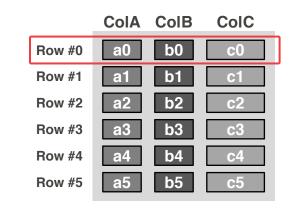


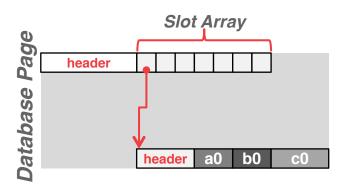
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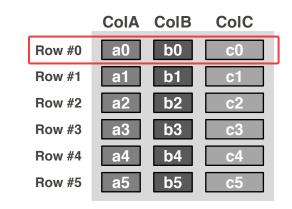


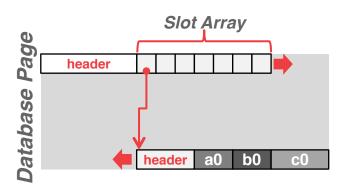
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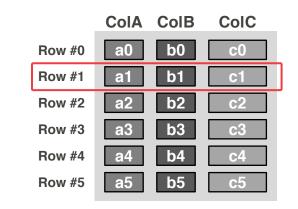


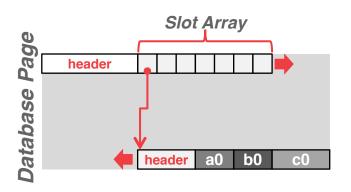
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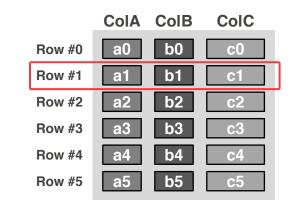


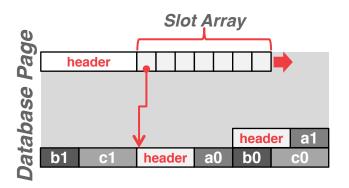
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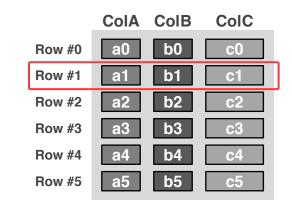


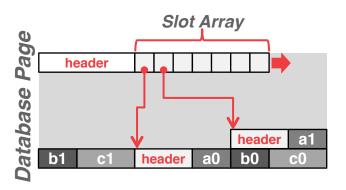
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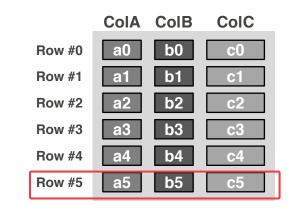


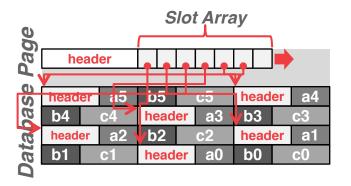
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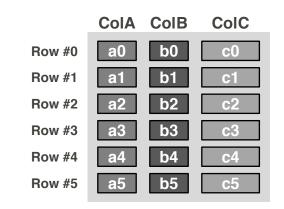


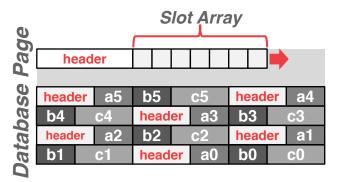
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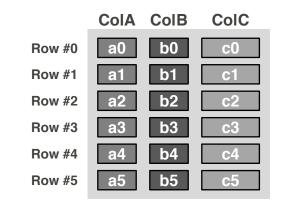
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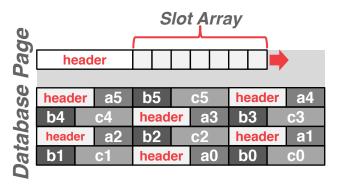




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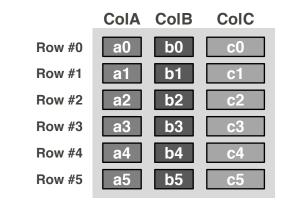
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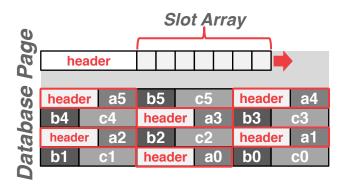




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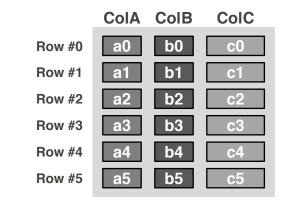


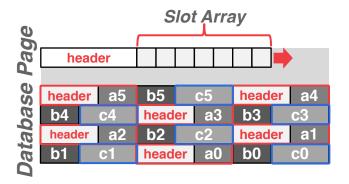


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N-ary Storage Model (NSM)

Advantages

- → Fast inserts, updates, and deletes.
- → Good for queries that need the entire tuple (OLTP).
- → Can use indexes for clustering.

Disadvantages

- → Not good for scanning large portions of the table and/or a subset of the attributes.
- → Terrible memory locality in access patterns.
- → Not ideal for compression because of multiple value domains within a single page.

Decomposition Storage Model (DSM)

The DBMS stores a single attribute for all tuples contiguously in a block of data.

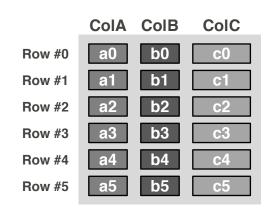
Ideal for OLAP workloads where read-only queries perform large scans over a subset of the table's attributes.

→ Use a batched *vectorized processing model*.

File sizes are larger (100s of MBs), but tuples might still be organized into smaller groups.

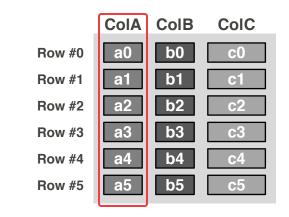
Store attributes and meta-data (e.g., nulls) in separate arrays of **fixed-length** values.

- → Most systems identify unique physical tuples using offsets into these arrays.
- → Need to handle variable-length values...



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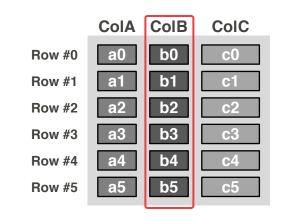
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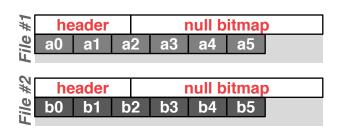




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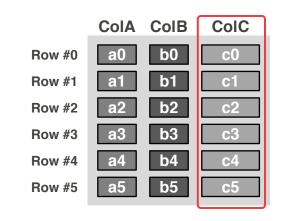
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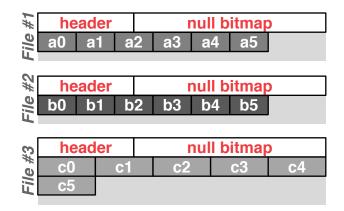




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DSM: Variable-Length Data

Padding variable-length fields to ensure they are fixed-length is wasteful, especially for large attributes.

A better approach is to use *dictionary compression* to convert repetitive variable-length data into fixed-length values (typically 32-bit integers).

→ More on this next class.

1970s: Cantor DBMS

1980s: DSM Proposal

1990s: SybaseIQ (in-memory only)

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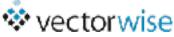
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Decomposition Storage Model (DSM)

Advantages

- → Reduces the amount of wasted I/O per query because the DBMS only reads the data that it needs.
- → Faster query processing because of increased locality and cached data reuse.
- → Better data compression (more on this next class).

Disadvantages

→ Slow for point queries, inserts, updates, and deletes because of tuple splitting/stitching/reorganization.

Observation

Observation

OLAP queries almost never access a single column in a table by itself.

→ At some point, the query must get other columns and stitch the original tuple back together.

But we still need to store data in a columnar format to get the storage + execution benefits.

We need a columnar scheme that still stores attributes separately but keeps the data for each tuple physically close together...

PAX Storage Model

Partition Attributes Across (PAX) is a hybrid storage model that vertically partitions attributes within a page.

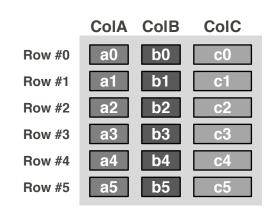
→ This is what Parquet and ORC use.

The goal is to get the benefit of <u>faster</u> processing on columns while retaining the <u>spatial locality</u> benefits of rows.

Horizontally partition rows into groups, then vertically partition their attributes into columns.

Global header contains directory with offsets to the file's row groups.

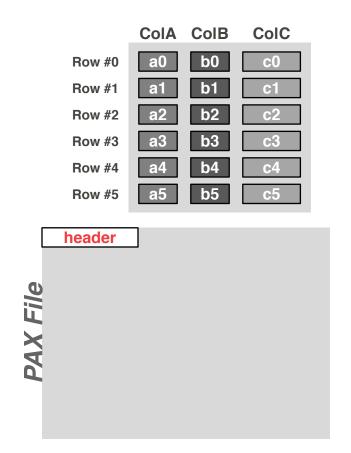
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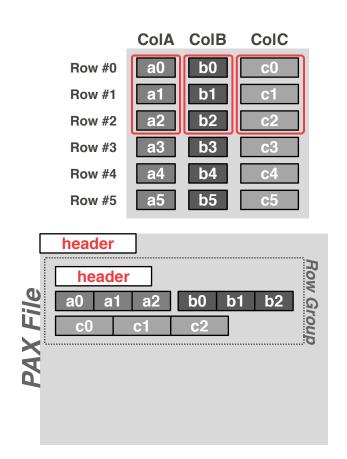
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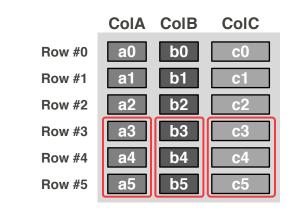
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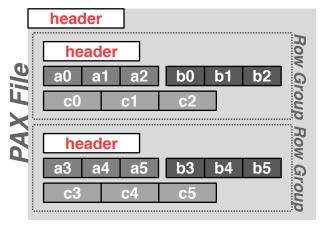


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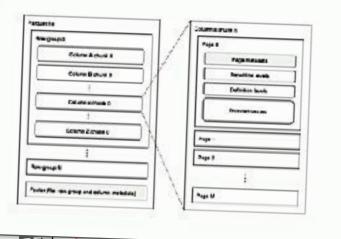
Global header conta with offsets to the fi

→ This is stored in the immutable (Parquet,

Each row group cometa-data header a contents.

Parquet: data organization

- Data organization
 - Row-groups (default 128MB);
 - o Column chunks
 - Pages (defauit 1MB)
 - Metadata
 - Min
 - Max
 - Count
 - Rep/def levels
 - Encoded values



databricks

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A DBMS uses a <u>buffer pool</u>, but why not use the OS instead?

With memory-mapped files, the OS is responsible for transparent paging of the file so the DBMS doesn't need to worry about it.

Is this a good idea?

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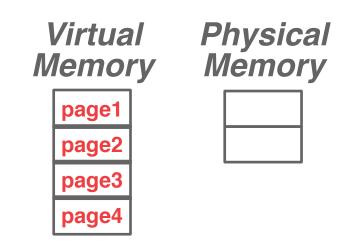
page1 page2 page3 page4

On-Disk File

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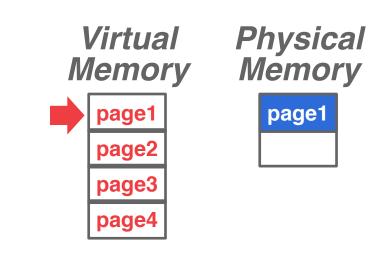




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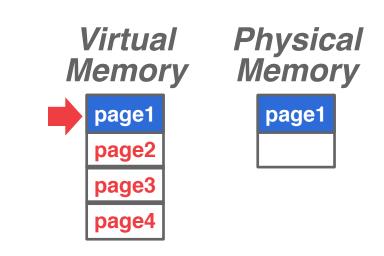
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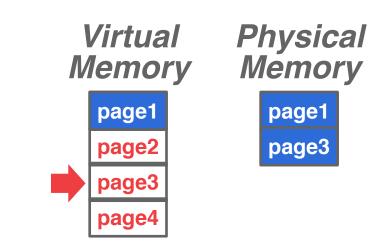
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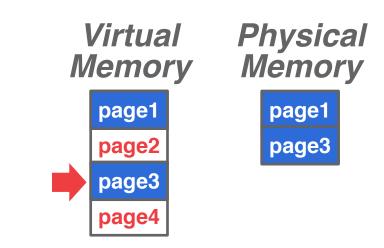




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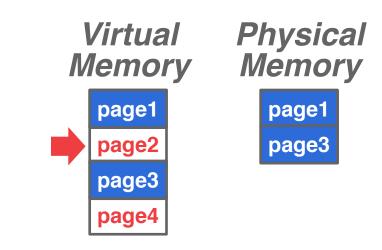
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page1

page2

page3

page4

Physical Memory

page1

page3

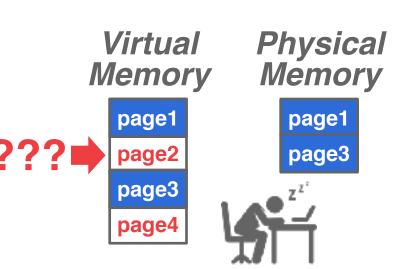


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page1 page2 page3 page4

On-Disk File

What if we allow multiple threads to access memory-mapped files to hide page fault stalls?

This works (well enough) for read-only access but becomes complicated with multiple writers.

Memory-Mapped Files

Problem #1: Transaction Safety

→ OS can flush dirty pages at any time.

Problem #2: I/O Stalls

→ DBMS doesn't know which pages are in memory. OS will stall a thread on page fault.

Problem #3: Error Handling

→ Difficult to validate pages. Any access can cause a SIGBUS that DBMS must handle.

Problem #4: Performance Issues

→ OS data structure contention. TLB shootdowns.

Data Representation

INTEGER/BIGINT/SMALLINT/TINYINT

→ C/C++ Representation

FLOAT/REAL vs. NUMERIC/DECIMAL

→ IEEE-754 Standard / Fixed-point Decimals

TIME/DATE/TIMESTAMP

→ 32/64-bit int of (micro/milli)seconds since Unix epoch

VARCHAR/VARBINARY/TEXT/BLOB

- → Pointer to other location if type is ≥64-bits
- → Header with length and address to next location (if segmented), followed by data bytes.
- → Most DBMSs use dictionary compression for these.

Inexact, variable-precision numeric type that uses the "native" C/C++ types.

Store directly as specified by <u>IEEE-754</u>.

→ Example: FLOAT, REAL/DOUBLE

These types are typically faster than fixed precision numbers because CPU ISA's have instructions / registers to support them.

But they do not guarantee exact values...

Rounding Example

```
#include <stdio.h>
int main(int argc, char* argv[]) {
   float x = 0.1;
   float y = 0.2;
   printf("x+y = %f\n", x+y);
   printf("0.3 = %f\n", 0.3);
}
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Output

```
x+y = 0.300000
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x+y = 0.300000
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```
x+y = 0.30000001192092895508
0.3 = 0.299999999999999999999
```

Fixed-Precision Numbers

Numeric data types with (potentially) arbitrary precision and scale. Used when rounding errors are unacceptable.

→ Example: **NUMERIC**, **DECIMAL**

Many different implementations.

- → Example: Store in an exact, variable-length binary representation with additional meta-data.
- → Can be less expensive if the DBMS does not provide arbitrary precision (e.g., decimal point can be in a different position per value).

Fixed-Precision Numbers

Numeric data type precision and scenarios are unacc

→ Example: NUME

Many different in

- → Example: Store representation v
- → Can be less exp arbitrary precisi different position per value).



We couldn't use the name "libfixedpoint" because it would be terrible for SEO...

3 PASSED

This is a portable C++ library for fixed-point decimals. It was originally developed as part of the NoisePage database project at Carnegie Mellon University.

This library implements decimals as 128-bit integers and stores them in scaled format. For example, it will store the decimal 12.23 with scale 5 1223eee. Addition and subtraction operations require two decimals of the same scale Decimal multiplication accepts an argument of lower scale and returns a decimal in the higher scale. Decimal division accepts an argument of the denominator scale and returns the decimal in numerator scale. A rescale decimal function is also provided.

Postgres: NUMERIC

```
typedef unsigned char NumericDigit;
typedef struct {
 int ndigits;
 int weight;
 int scale;
 int sign;
 NumericDigit *digits;
 numeric;
```

Postgres: NUMERIC

of Digits

Weight of 1st Digit

Scale Factor

Positive/Negative/NaN

Digit Storage

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```
add var() -
                                 Full version of add functionality on variable level (handling signs).
                                 result might point to one of the operands too without danger.
                             PSTYPEShumeric add(numeric *var1, numeric *var2, numeric *result)
                                 * Decide on the signs of the two variables what to do
                                 it (Vari >sign -- NUMERIC POS)
                                    i[ (var2 ⇒sign -- NUMERIC POS)
                                        * Noth are positive result = +(ANS(var1) + ANS(var2))
                                                                                                                 NumericDigit
                                        1f (add_abs(yar1, yar2, result) != 6)
                                       result >sign = NUMERIC POS:
                                   )
else
         Weight of

    varl is positive, var2 is negative Must compare absolute values

                                       switch (cmp abs(var1, var2))
                                           CHERT
                   Sca
                                               * ABS(var1) -- ABS(var2)
                                                 result = ZEBO
                                              zero_var(result);
                                              result-spacale = Max(var1-spacale, var2-spacale);
                                              result-schoole = Max(vart-schoole, var2-schoole);
Positive/Nega
                                          case 1:
                                                ABS(var1) > ABS(var2)
                                                result = +(ABS(var1) - ABS(var2))
                                             if (sub_abs(var1, var2, result) != 0)
                                                 return 1;
                                             result >sign = NUMERIC FOS;
                                               ABS(var1) < ABS(var2)
                                               result = (ABS(var2)
```

ABS(var1))

MySQL: NUMERIC

```
typedef int32 decimal_digit_t;
struct decimal_t {
  int intg, frac, len;
  bool sign;
  decimal_digit_t *buf;
};
```

MySQL: NUMERIC

```
# of Digits Before Point
```

of Digits After Point

Length (Bytes)

Positive/Negative

Digit Storage

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```
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struct decimal_t {
  int intg, frac, lon,
  bool sig n;
decimal_digit_t buf;
};
```

```
static int do_add(const decimal_t *from1, const decimal_t *from2,
                           decimal_t *to) {
           int intg1 = ROUND_UP(from1->intg), intg2 = ROUND_UP(from2->intg),
                frac1 = ROUND_UP(from1->frac), frac2 = ROUND_UP(from2->frac),
                frac0 = std::max(frac1, frac2), intg0 = std::max(intg1, intg2), error;
            dec1 *buf1, *buf2, 'buf0, *stop, *stop2, x, carry;
             sanity(to);
             /* is there a need for extra word because of carry ? */
# of
                                                                                                       digit_t;
             x = intg1 > intg2
                     : intg2 > intg1 ? from2->buf[0] : from1->buf[0] + from2->buf[0];
              if (unlikely(x > DIG_MAX - 1)) /* yes, there is */
                intg0++;
                to->buf[0] = 0; /' safety */
               FIX_INTG_FRAC_ERROR(to->len, intg0, frac0, error);
               if (unlikely(error == E_DEC_OVERFLOW)) {
                 max_decimal(to->len * DIG_PER_DEC1, 0, to);
                 return error;
                buf0 = to->buf + intg0 + frac0;
                to->sign = from1->sign;
                to->frac = std::max(from1->frac, from2->frac);
                         total * atg PER DEC1;
```

NULL Data Types

Choice #1: Special Values

→ Designate a value to represent NULL for a data type (e.g., INT32_MIN).

Choice #2: Null Column Bitmap Header

→ Store a bitmap in a centralized header that specifies what attributes are null.

Choice #3: Per Attribute Null Flag

- → Store a flag that marks that a value is null.
- → Must use more space than just a single bit because this messes up with word alignment.

NULL Data Types

Integer Numbers

Data Type	Size	Size (Not Null)	Synonyms	Min Value	Max Value
BOOL	2 bytes	1 byte	BOOLEAN	0	1
BIT	9 bytes	8 bytes			
TINYINT	2 bytes	1 byte		-128	127
SMALLINT	4 bytes	2 bytes		-32768	32767
MEDIUMINT	4 bytes	3 bytes		-8388608	8388607
INT	8 bytes	4 bytes	INTEGER	-2147483648	2147483647
BIGINT	12 bytes	8 bytes		-2 ** 63	(2 ** 63) - 1
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Observation

Data is "hot" when it enters the database.

→ A newly inserted tuple is more likely to be updated again in the near future.

As a tuple ages, it is updated less frequently.

→ At some point, a tuple is only accessed in read-only queries along with other tuples.

HTAP Storage Model

Use separate execution engines that are optimized for either NSM or DSM databases.

- → Store new data in NSM for fast OLTP.
- → Migrate data to DSM for more efficient OLAP.
- → Combine query results from both engines to appear as a single logical database to the application.

Choice #1: Fractured Mirrors

→ Examples: Oracle, IBM DB2 Blu, Microsoft SQL Server

Choice #2: Delta Store

→ Examples: SAP HANA, Vertica, SingleStore, Databricks, Google Napa

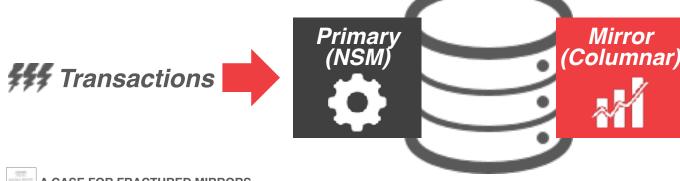
- → All updates are first entered in NSM then eventually copied into DSM mirror.
- → If the DBMS supports updates, it must invalidate tuples in the DSM mirror.



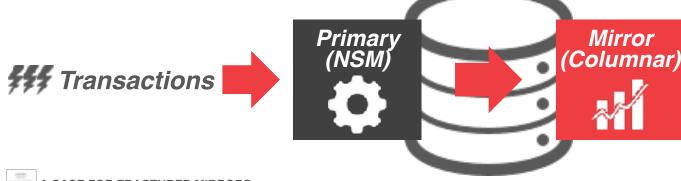
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Delta Store

Stage updates in an NSM table.

A background thread migrates updates from delta store and applies them to DSM data.

→ Batch large chunks and then write them out as a PAX file.



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Database Partitioning

Split database across multiple resources:

- → Disks, nodes, processors.
- → Often called "sharding" in NoSQL systems.

The DBMS executes query fragments on each partition and then combines the results to produce a single answer.

The DBMS can partition a database **physically** (shared nothing) or **logically** (shared disk).

Horizontal Partitioning

Split a table's tuples into disjoint subsets based on some partitioning key and scheme.

→ Choose column(s) that divides the database equally in terms of size, load, or usage.

Partitioning Schemes:

- → Hashing
- → Ranges
- → Predicates

Parting Thoughts

Every modern OLAP system is using some variant of PAX storage. Ideally, all data should be **fixed-length**.

Real-world tables contain mostly numeric attributes (int/float), but their occupied storage is mostly comprised of string data.

Modern columnar systems are so fast that most people do <u>not</u> denormalize data warehouse schemas.

Next Class

Compression