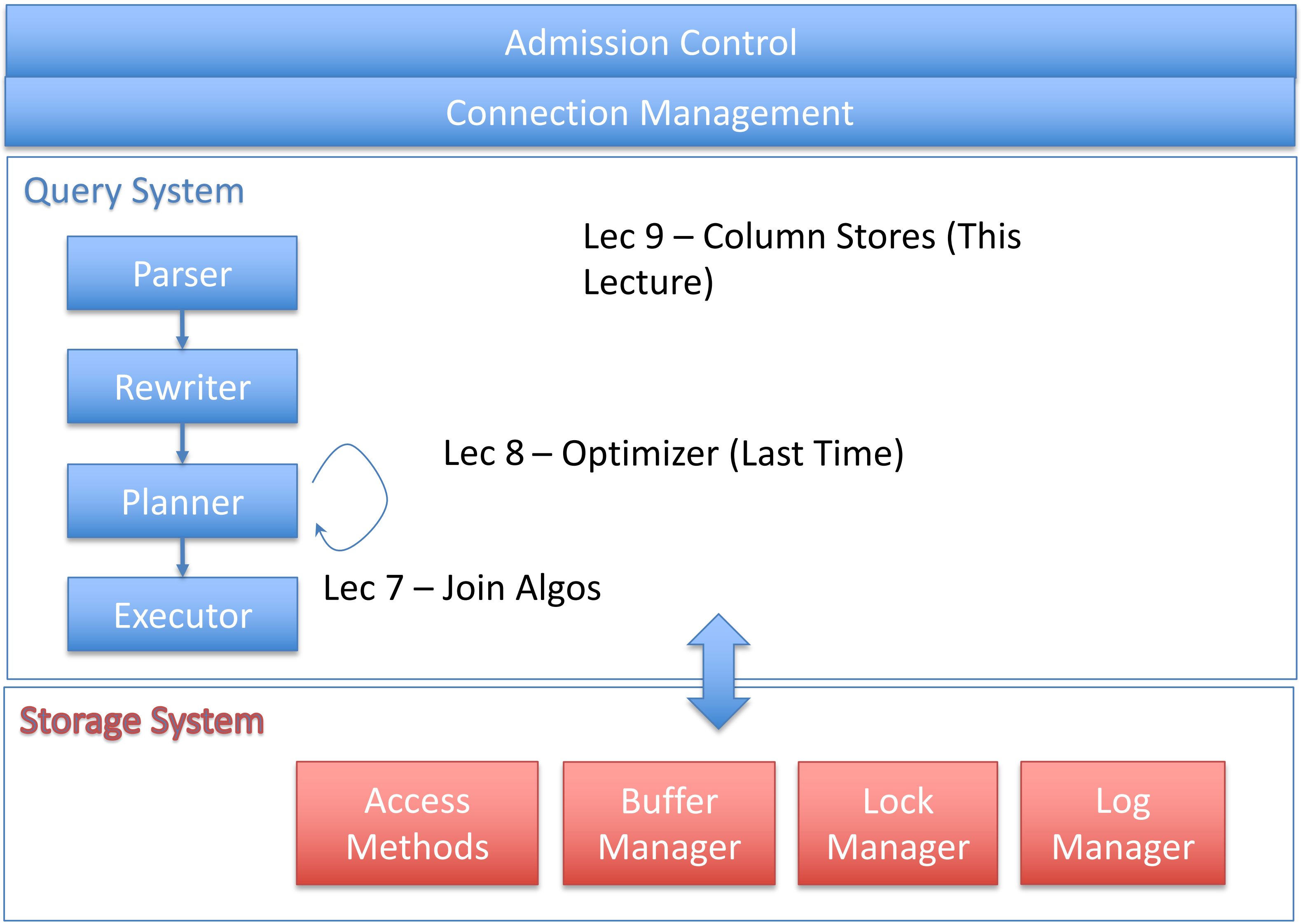
6.5830 Lecture 9

Column Stores

10/4/2023

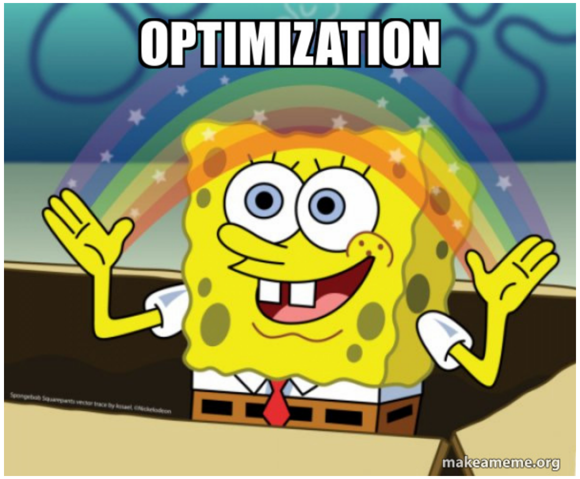
PS2 Due 10/10

Plan for Next Few Lectures



Optimization Recap

- Selinger Optimizer is the foundation of modern cost-based optimizers
  - Simple statistics
  - Several heuristics, e.g., left-deep
  - Dynamic programming algo for join ordering
- Easy to extend, e.g., with:
  - More sophisticated statistics
  - Fewer heuristics

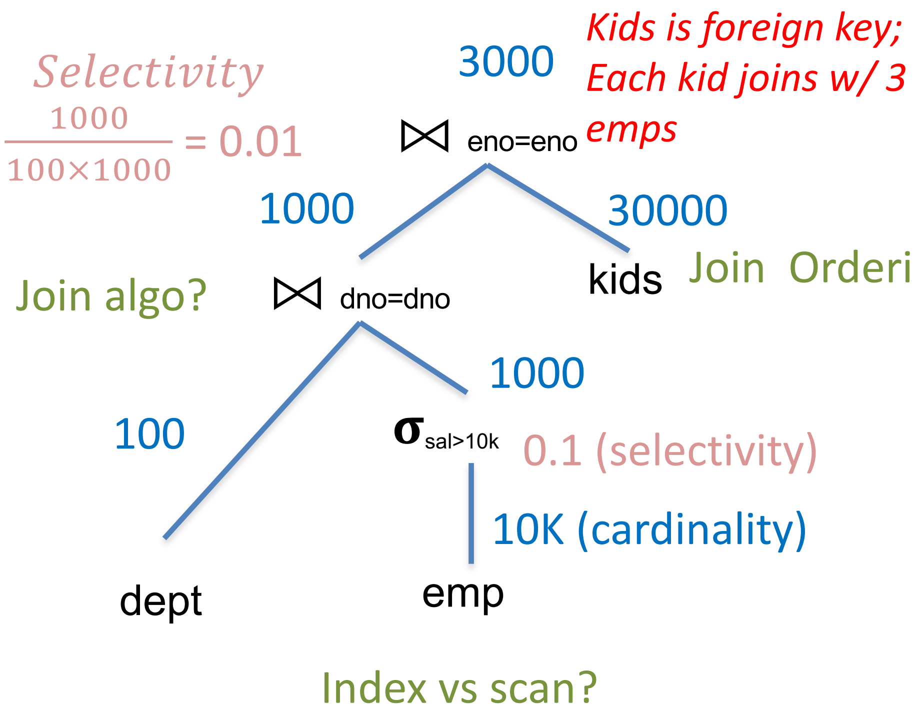


Optimization Steps

SELECT * FROM emp, dept, kids
WHERE sal > 10k
AND emp.dno = dept.dno
AND emp.eid = kids.eid

100 tuples/page
10 pages RAM
10 KB/page

|dept| = 100 records = 1 page = 10 KB
|emp| = 10K = 100 pages = 1 MB
|kids| = 30K = 300 pages = 3 MB



Join Ordering? Why not kids / emp first?

Steps:

For each plan alternative:

1. Estimate sizes of relations
2. Estimate selectivities
3. Compute intermediate sizes
4. Evaluate cost of plan operations

5. Select best plan

Today: Column Stores

A different way to build a database system

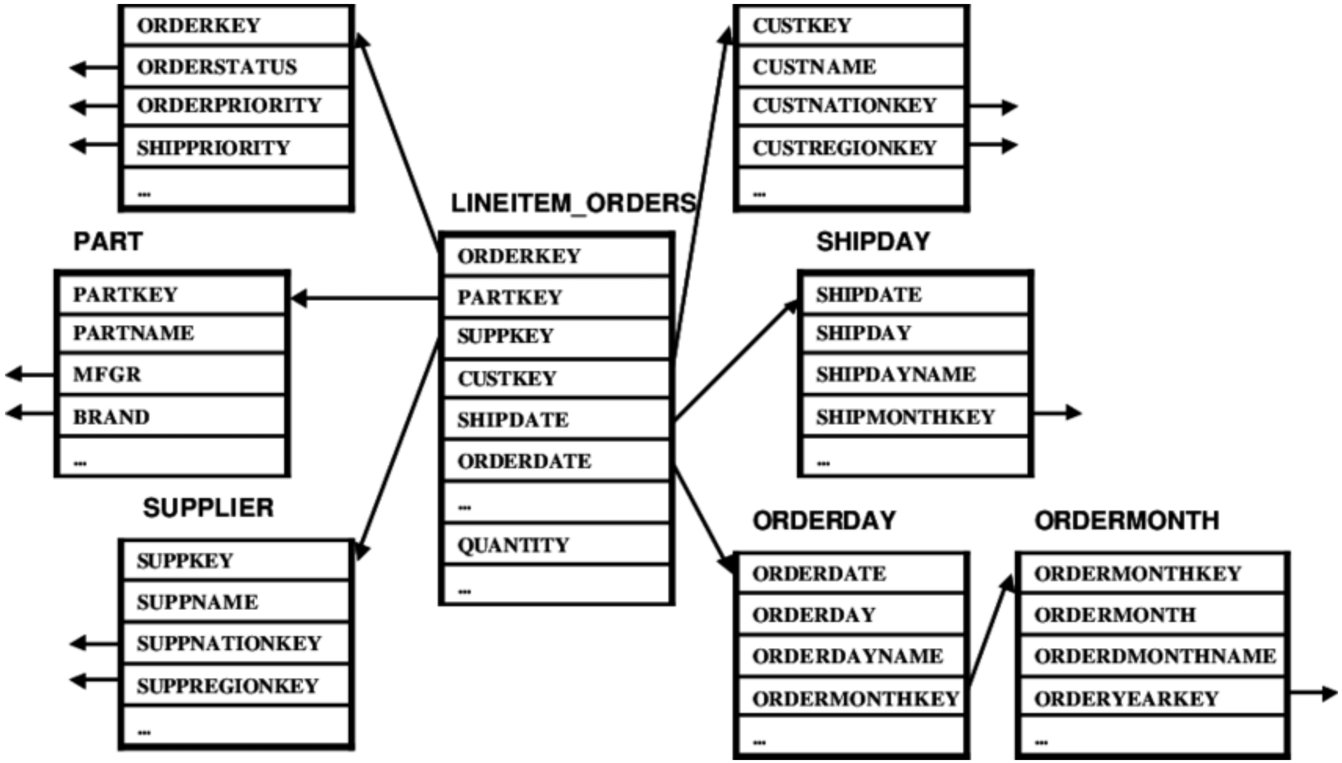
Typical Database Setup

"Extract, Transform, Load"

Transactional database
Lots of writes/updates
Reads of individual records

Analytics / Reporting Database
"Warehouse"
Lots of reads of many records
Bulk updates
Typical query touches a few columns

Example Warehouse: TPC-H



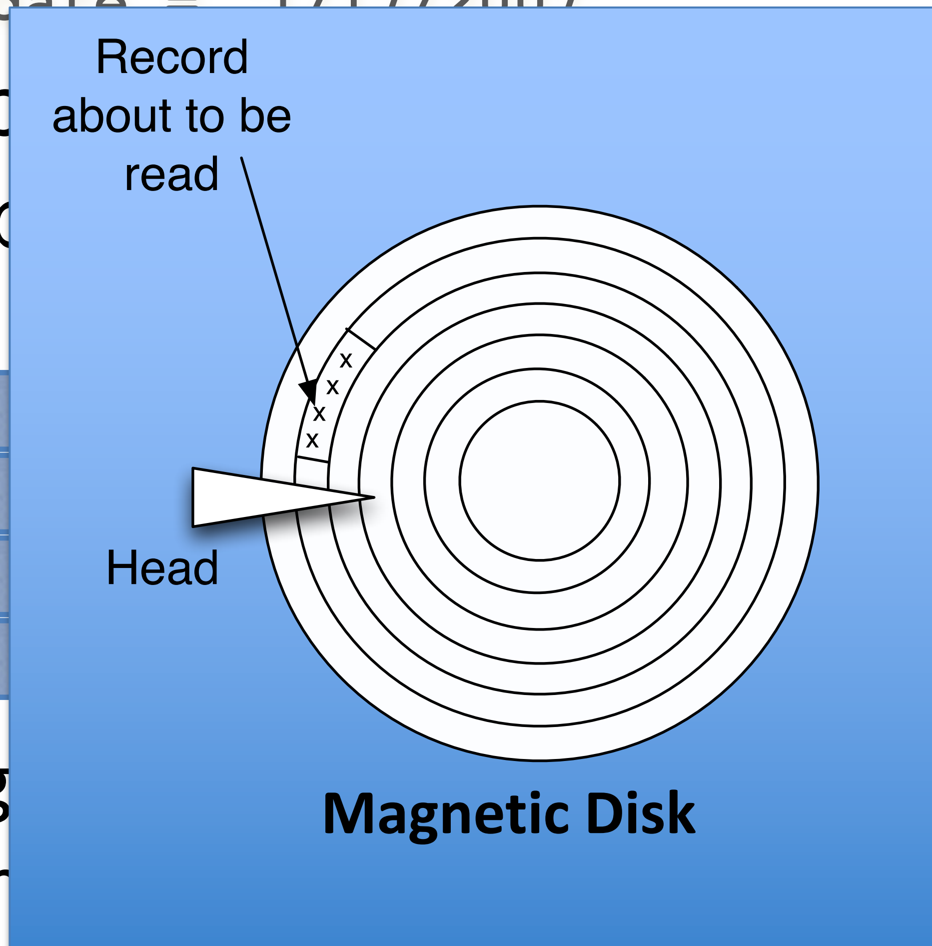
All use through lineitem_orders – I.e., products purchased by day, or by customer …

“star schema”

How Long Does a Scan Take?

```
SELECT avg(price) FROM tickstore  WHERE symbol =
'GM'  and date = '1/17/2007'
```

- Time p data read
- Examp



change	date
YSE	1/17/2007
YSE	1/17/2007
YSE	1/17/2007
QDS	1/17/2007

Even thoug and *symbol*, if data is or lumns

Memory and SSD also transfer a block at a time, so same issue arises.

Column Representation Reduces Scan Time

- Idea: Store each column in a separate file

Column Representation

Reads Just 3 Columns

GM	30.77	1,000	NYSE	1/17/2007
GM	30.77	10,000	NYSE	1/17/2007
GM	30.78	12,500	NYSE	1/17/2007
AAPL	93.24	9,000	NQDS	1/17/2007

Assuming each column is same size, reduces bytes read from disk by factor of 3/5

In reality, databases are often 100's of columns

Linearizing a Table – Row store

C1	C2	C3	C4	C5	C6

Memory/Disk
(Linear Array)

R1 C1
R1 C2
R1 C3
R1 C4
R1 C5
R1 C6
R2 C1
R2 C2
R2 C3
R2 C4
R2 C5
R2 C6
R3 C1
R3 C2
R3 C3
R3 C4
R3 C5
R3 C6
R4 C1
R4 C2
R4 C3
R4 C4
R4 C5
R4 C6

Linearizing a Table – Column Store

C1	C2	C3	C4	C5	C6

<u>Memory/Disk</u>
<u>(Linear Array)</u>

R1 C1
R2 C1
R3 C1
R4 C1
R5 C1
R6 C1
R1 C2
R2 C2
R3 C2
R4 C2
R5 C2
R6 C2
R1 C3
R2 C3
R3 C3
R4 C3
R5 C3
R6 C3
R1 C4
R2 C4
R3 C4
R4 C4
R5 C4
R6 C4

Tables Often Super Wide

- Data warehouse at Cambridge Mobile Telematics

Table	#columns
t1	251
t2	248
t3	134
t4	107
t5	87
t6	83
t7	71
t8	54
t9	52
t10	45

Average query access 4-5 fields

Top 2-3 tables involved in nearly every query

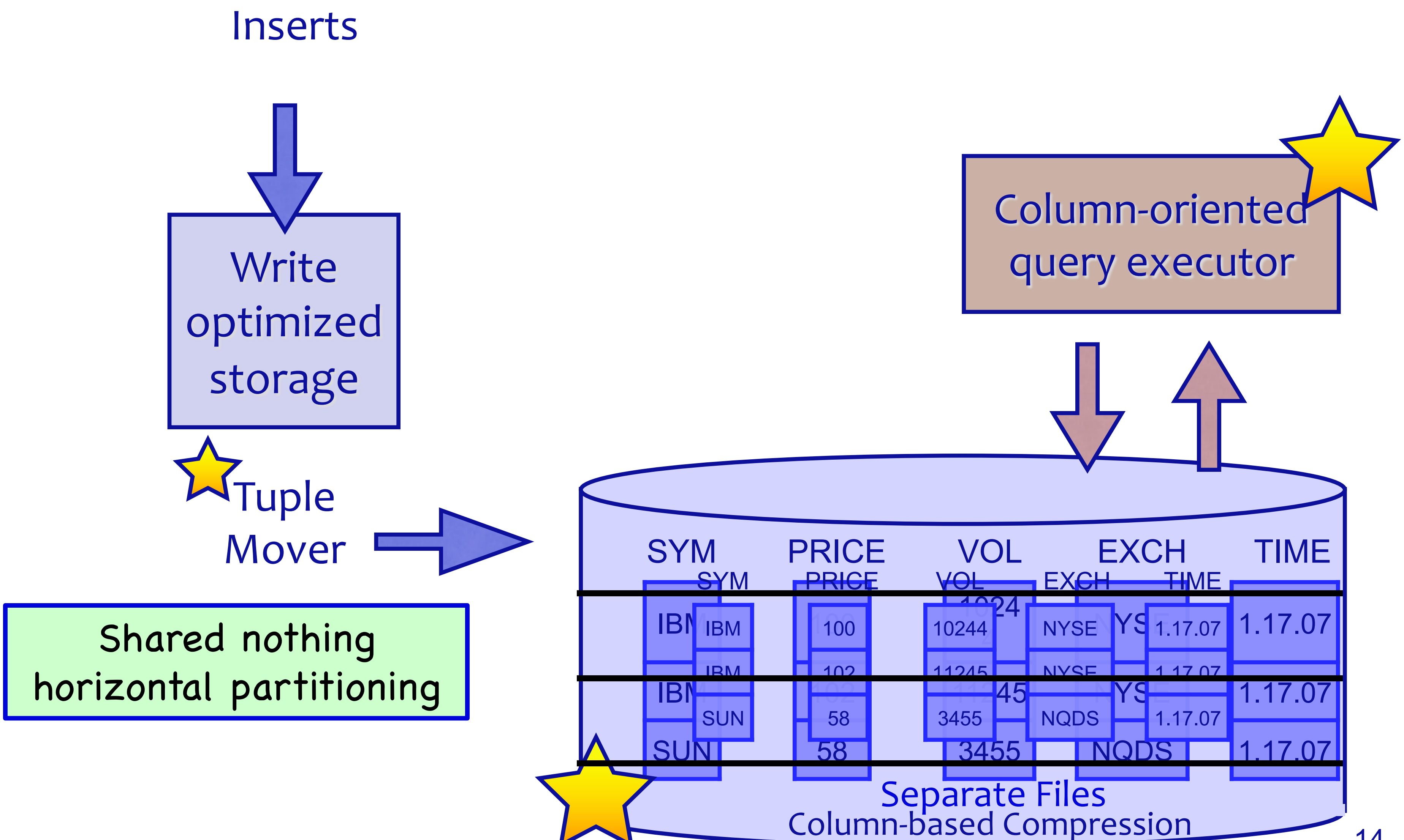
Using a row-store would impose ~200/4 = 50x performance overhead

When Are Columns Right?

- **Warehousing** (OLAP)
  - Read-mostly; batch update
  - Queries: Scan and aggregate a few columns
- Vs. Transaction Processing (OLTP)
  - Write-intensive, mostly single record ops.
- **Column-stores: OLAP optimized**
- In practice >10x performance on comparable HW, for many real world analytic applications
  - True even if w/ Flash or main memory!

Different architectures for different workloads

C-Store: Rethinking Database Design from the Ground Up

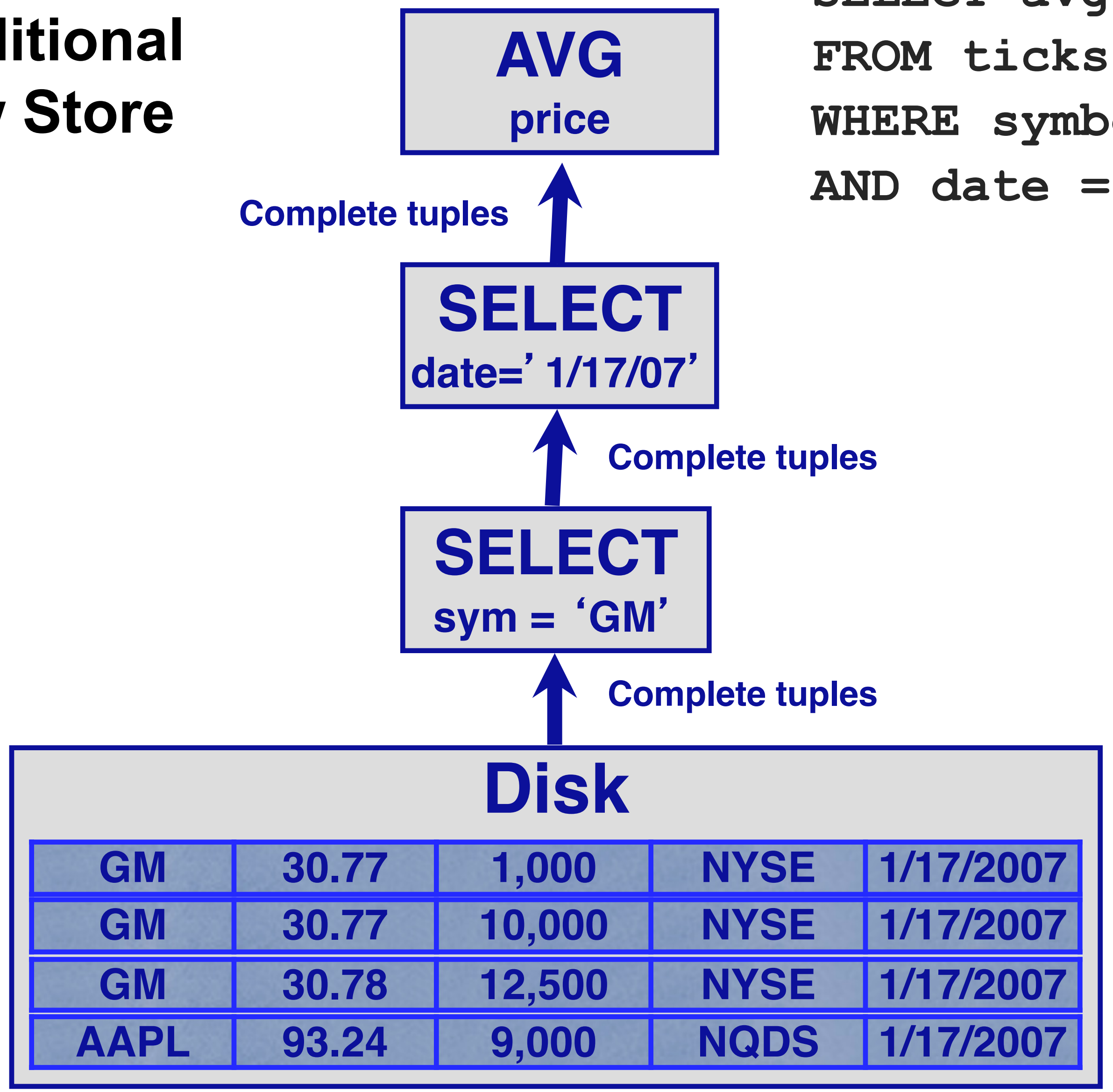


"C-Store: A Column-oriented DBMS" -- VLDB 05

Query Processing Example

- **Traditional Row Store**

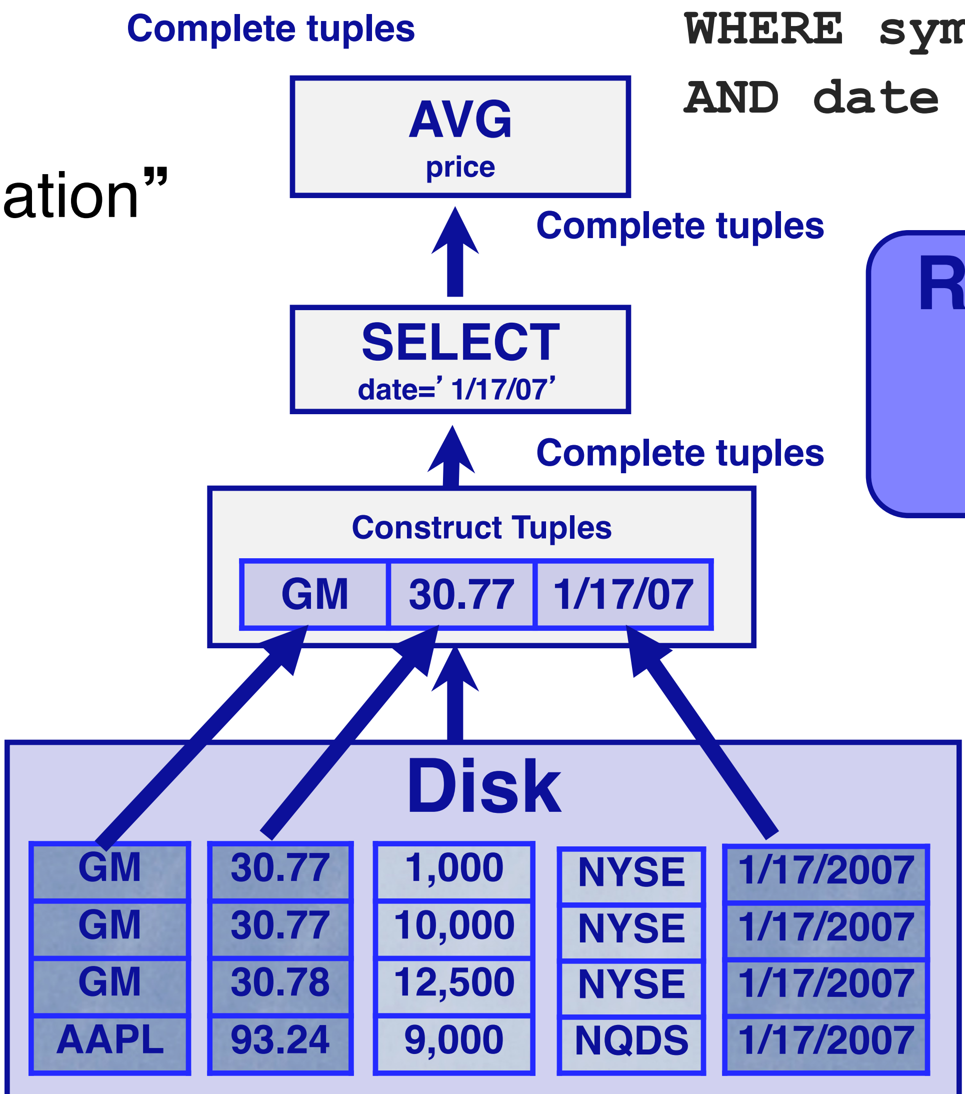
```
SELECT avg(price)
FROM tickstore
WHERE symbol = 'GM'
AND date = '1/17/2007'
```



Query Processing Example

- **Basic Column Store**
- "Early Materialization"

```
SELECT avg(price)
FROM tickstore
WHERE symbol = 'GM'
AND date = '1/17/2007'
```

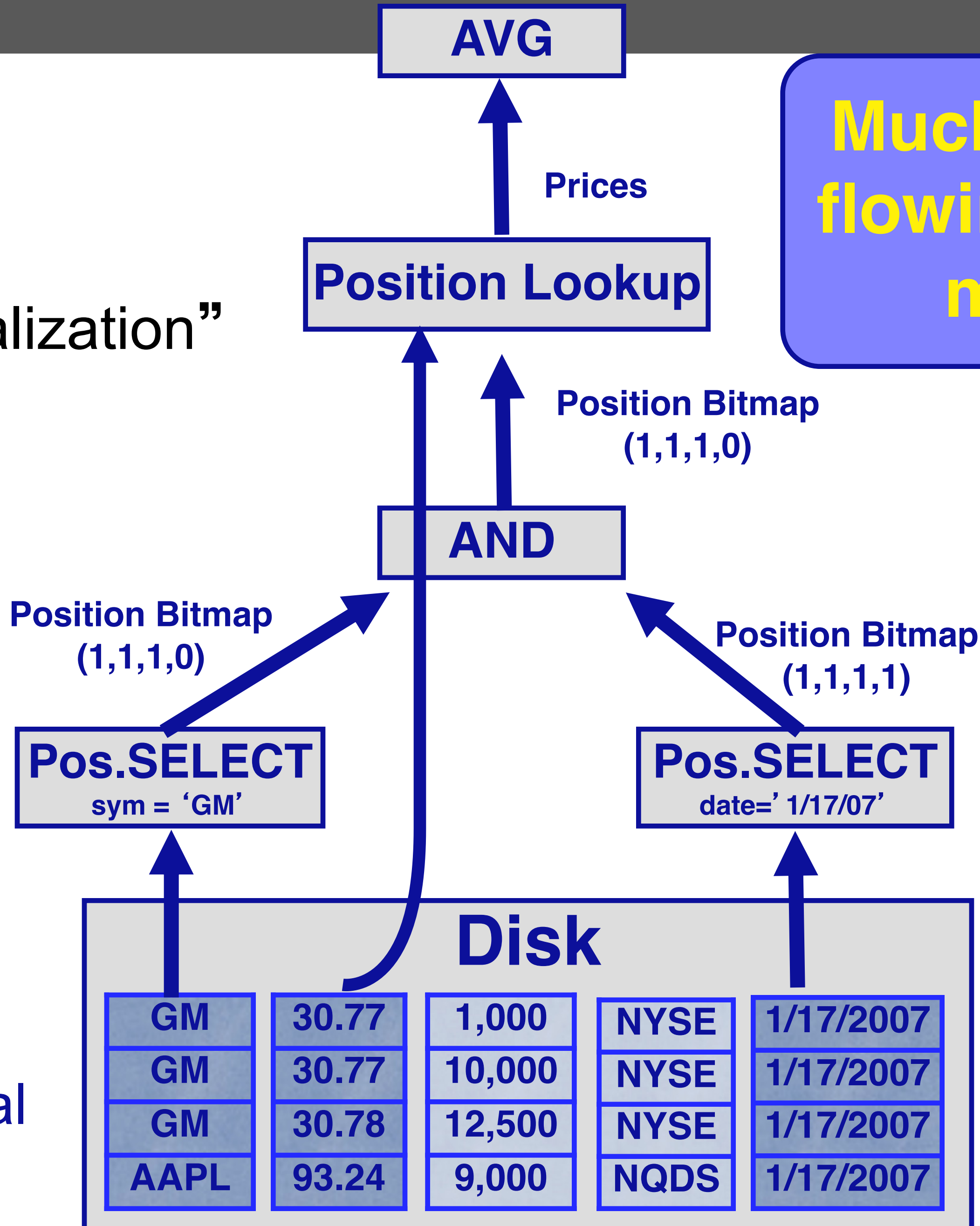


Row-oriented plan

Fields from same tuple at same index (position) in each column file

Query Processing Example

- **C-Store**
  - "Late Materialization"



Much less data flowing through memory

See Abadi et al ICDE 07

Why Compress?

- **Database** size is 2x-5x larger than the volume of data loaded into it
- Database performance is proportional to the amount of data flowing through the system

Abadi et al, SIGMOD 06

Column-Oriented Compression

- Query engine processes compressed data
- Transfers load from disk to CPU
- Multiple compression types
  - Run-Length Encoding (RLE), LZ, Delta Value, Block Dictionary Bitmaps, Null Suppression
- System chooses which to apply
- Typically see 50% - 90% compression
- NULLs take virtually no space

Columns contain similar data, which makes compression easy

RLE	Delta	LZ	RLE	RLE
3xGM	30.77	1,000	3xNYSE	4 x 1/17/2007
1XAPPL	30.77	10,000	1XNQDS	1/17/2007
GM	30.78	12,500 9,000	NYSE	1/17/2007
AAPL	93.24	9,000	NQDS	1/17/2007

Run Length Encoding

- Replace repeated values with a count and a value
- For single values, use a run length of 1
  - Naively, can increase storage space
  - Can use a shorter bit sequence for 1s, at the cost of more expensive decompression
- E.g., 1110002 → 3x1, 3x0, 1x2
- Works well for mostly-sorted, few-valued columns

Dictionary Encoding

- Many variants; simplest is to replace string values with integers and maintain a dictionary
- I.e., AAPL, AAPL, IBM, MSFT →

  1,1,2,3   +   1:AAPL, 2:IBM, 3:MSFT
- Works well for few-valued string columns
  - Choice of dictionary not obvious
  - Words? Records?

Lempel Ziv Encoding

- LZ (“Lempel Ziv”) Compression
- General purpose lossless data compression
- Builds data dictionary dynamically as it runs
  - Add new bit strings to the dictionary as they are encountered
- Treat entire column as a document

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16

Output:

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16

Output: 1

LZ Example

- $\boxed{\text{AA}}$PLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27

Output: 1

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28

Output: 1 1

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28

Output: 1 1 16

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28, PL: 29

Output: 1 1 16 12

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28, PL: 29, LA: 30

Output: 1 1 16 12

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28, PL: 29, LA: 30

Output: 1 1 16 12 27

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28, PL: 29, LA: 30, AAP:31

Output: 1 1 16 12 27

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28, PL: 29, LA: 30, AAP:31

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Output: 1 1 16 12 27 29

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28, PL: 29, LA: 30, AAP:31, PLI: 32, LI: 33, IB: 34

Output: 1 1 16 12 27 29 9

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28, PL: 29, LA: 30, AAP:31, PLI: 32, LI: 33, IB: 34, BM: 35

Output: 1 1 16 12 27 29 9 2

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28, PL: 29, LA: 30, AAP:31, PLI: 32, LI: 33, IB: 34, BM: 35, MA:36

Output: 1 1 16 12 27 29 9 2 13

LZ Example

- AAPLAAPLIBM$\boxed{\text{AAP}}$L

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28, PL: 29, LA: 30, AAP:31, PLI: 32, LI: 33, IB: 34, BM: 35, MA:36

Output: 1 1 16 12 27 29 9 2 13

LZ Example

- AAPLAAPLIBMAAPL

Dictionary: A:1, B:2, … ,F:6, … ,I:9, …, L:12, M:13, …, P:16, .., AA:27, AP:28, PL: 29, LA: 30, AAP:31, PLI: 32, LI: 33, IB: 34, BM: 35, MA:36

Output: 1 1 16 12 27 29 9 2 13 31

LZ Example

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LZ Example

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LZ Example

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Output: 1 1 16 12 27 29 9 2 13 31 12

Reduced from 15 to 11 symbols

But future AAPL patterns will be emitted as 1 byte instead of 4

Dictionary can be further encoded, e.g., using entropy encoding to make most common patterns use least bits ("Huffman encoding")

Bit Packing

- Encode values with fewest possible bits
- Each value becomes bit-length (e.g., 0-8 or 0-32), followed by value in that many bits
- E.g.,: 1 2 37 7
  - Need 1, 2, 6, and 3 bits respectively
  - Each number becomes 3 bit header and encoded value
    - `1:      0x001, 0x1`
    - `2:      0x010, 0x10`
    - `37:     0x110, 0x100101`
    - `7:      0x011, 0x111`
  - 3 x 4 + 12 = 24 bits to encode, vs e.g., 8x4 = 32

Delta Encoding

- Consecutive values encoding as difference to previous values
- 1.1, 1.2, 1.3 → 1.1, +.1, +1
  - After encoding as deltas, bit-pack
  - Works if deltas can be represented in fewer bits than whole values
- Works well for e.g., floats with small variations

Bitmap Encoding

- Encode few valued columns as bitmaps
- M M M F F → 11100, 00011
  - If fewer distinct values than bitwidth of field, saves space
  - Bitmaps can be further compressed, e.g., using RLE
- Bitmaps are very good for certain kinds of operations, e.g., filtering

Sorted Data

- Delta and RLE work great on sorted data
- Trick: Secondary sorting

X	Y
a	2
b	2
a	1
b	1

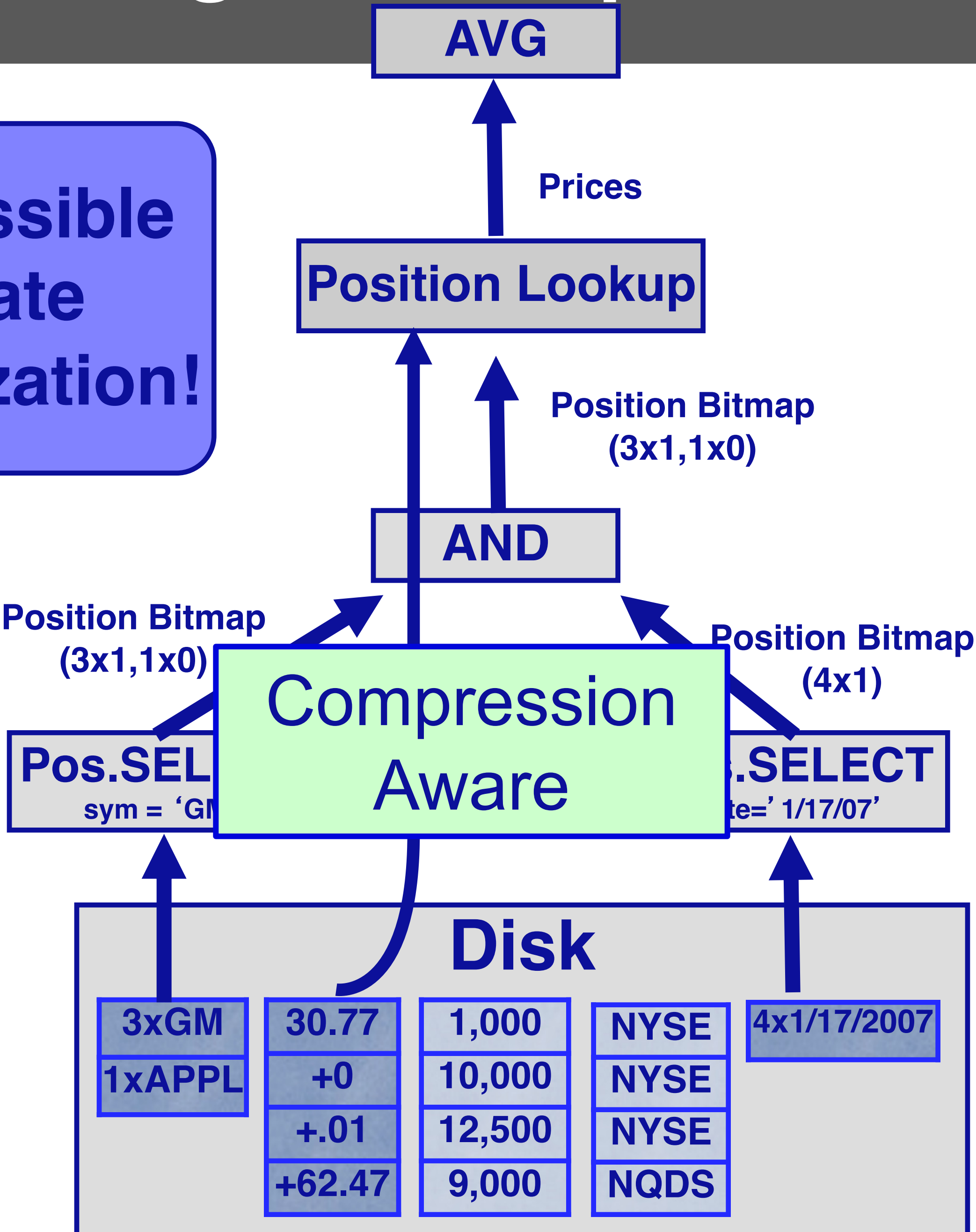
Sort on X, then Y →

X	Y
a	1
a	2
b	1
b	2

Y is not sorted, but if many duplicates of X, will be “mostly” sorted

Operating on Compressed Data

Only possible with late materialization!



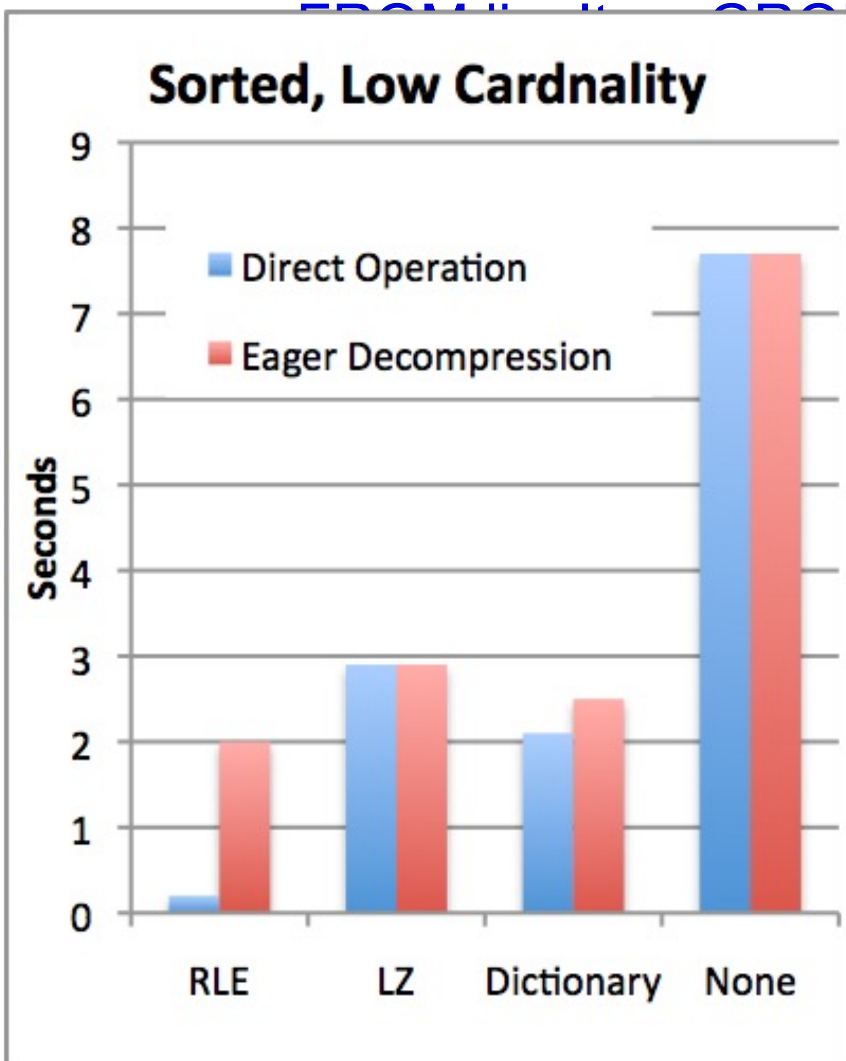
Direct Operation Optimizations

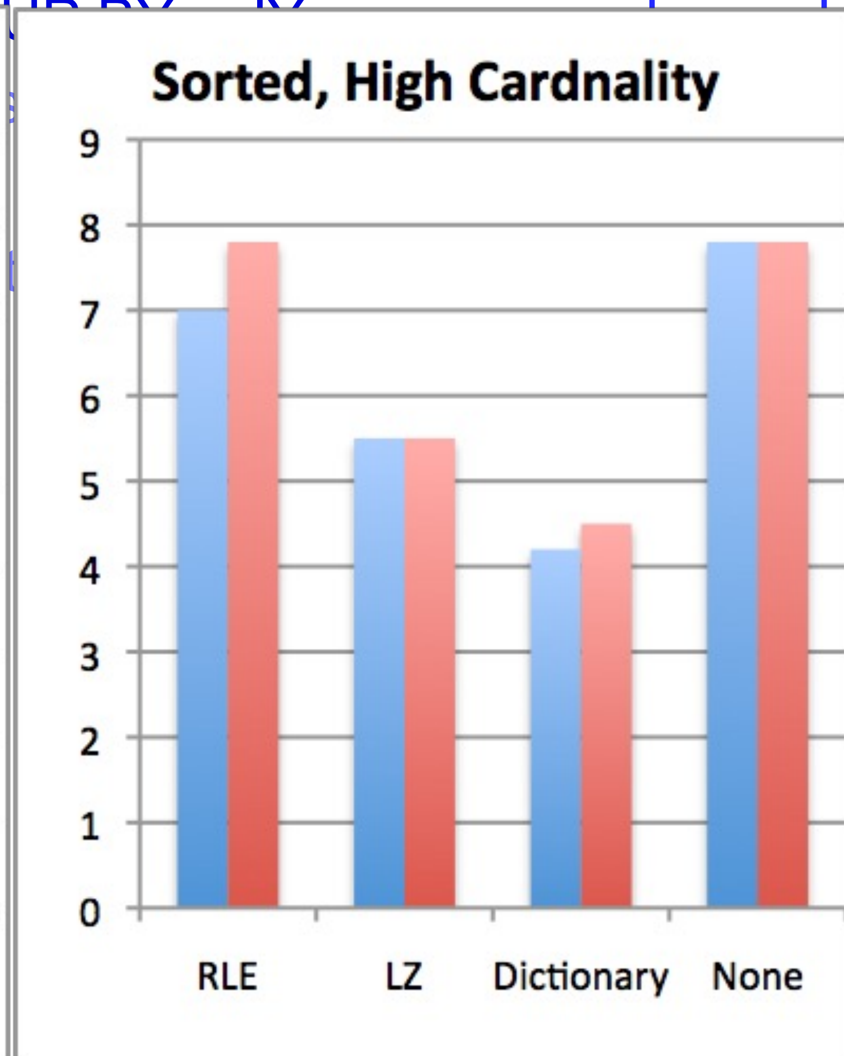
- Compressed data used directly for position lookup
  - RLE, Dictionary, Bitmap
- Direct Aggregation and GROUP BY on compressed blocks
  - RLE, Dictionary
- Join runs of compressed blocks
  - RLE, Dictionary
- Min/max directly extracted from sorted data

TPC-H Compression Performance

- Query: SELECT colY, SUM(colX)

Y	X
1	A
	C
	D
	B
	C
	A





Compression + Sorting is a Huge Win

- How can we get more sorted data?
- **Store duplicate copies of data**
    - Use different physical orderings

- Improves ad-hoc query performance
    - Due to ability to directly operate on sorted, compressed data

- Supports fail-over / redundancy

Study Break: Compression

- For each of the following columns, what compression method would you recommend?

(Choose from **A.** RLE, **B.** Dictionary, **C.** Bitmap**, D.** Delta, **E.** Bit-packing)

https://clicker.mit.edu/6.5830/

An unsorted column of integers in the range 0-100

Delta/Bit-packing (LZ/dictionary also OK)

A mostly sorted column of arbitrary strings

LZ

A mostly sorted column of integers in the range 0-10

RLE

A sorted column of floats

Delta

An unsorted column of strings w/ 3 values

Bitmap

Write Performance

Trickle load: Very Fast Inserts

> **Write-optimized Column Store (WOS)**

Memory: mirrored projections in insertion order (uncompressed)

Tuple Mover

Asynchronous Data Movement

Batched

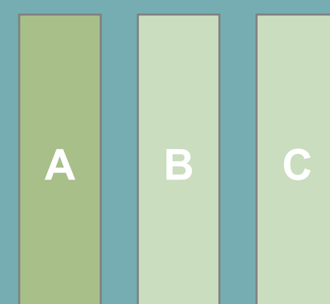
Amortizes seeks

Amortizes recompression

Enables continuous load

> **Read-optimized Column Store (ROS)**

Disk: data is sorted and compressed



(A B C | A)

Queries read from both WOS and ROS

When to Rewrite ROS Objects?

- Store multiple ROS objects, instead of just one
  - Each of which must be scanned to answer a query
- Tuple mover writes new objects
  - Avoids rewriting whole ROS on merge
- Periodically merge ROS objects to limit number of distinct objects that must be scanned ("Log structured merge tree")

Problem: Lots of Partitions

- Performance will degrade as you get many partitions
- Idea: merge some partitions together, but how?

- Log structured merge tree: arrange so partitions merge a logarithmic number of times

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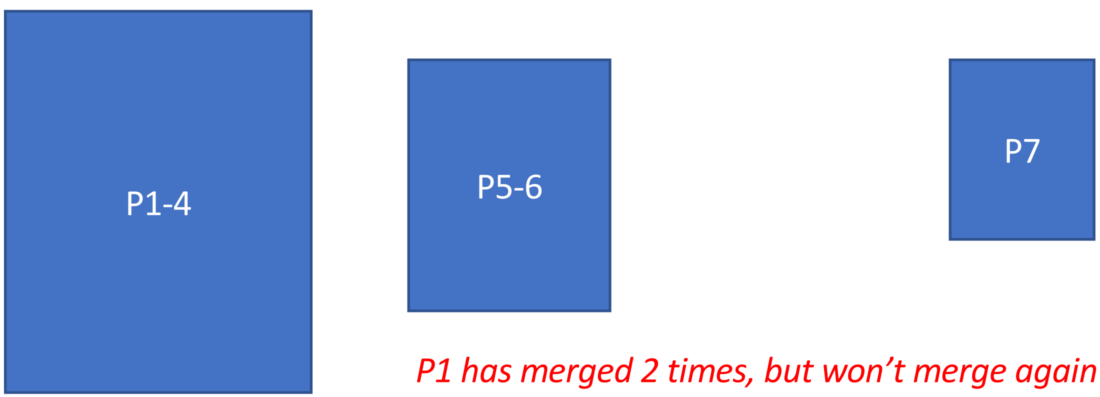
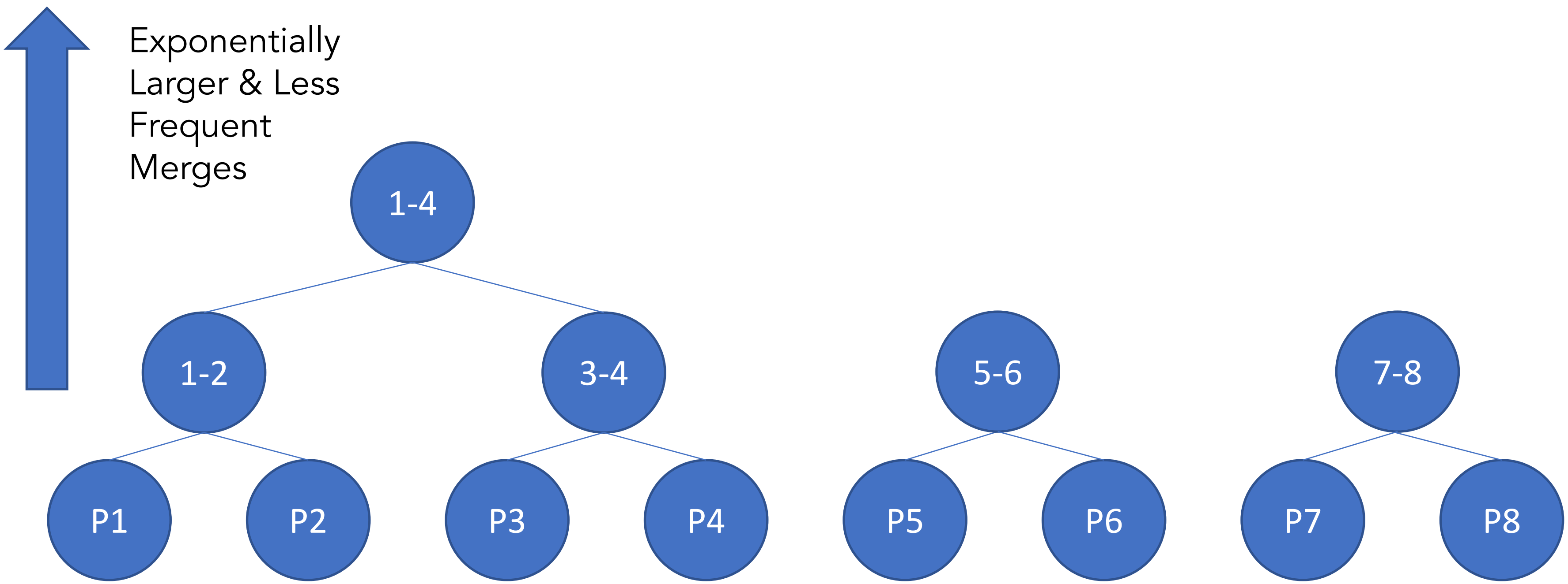


P1 has merged 2 times, but won't merge again until after 8 more partitions arrive

Log Structure Merge Tree



Column-Oriented Data In Modern Systems

- C-Store commercialized as Vertica
- Although it wasn’t the first column-oriented DB, it led to a proliferation of commercial column-oriented systems
- Now the de-facto way that analytic database systems are built, including Snowflake, Redshift, and others.

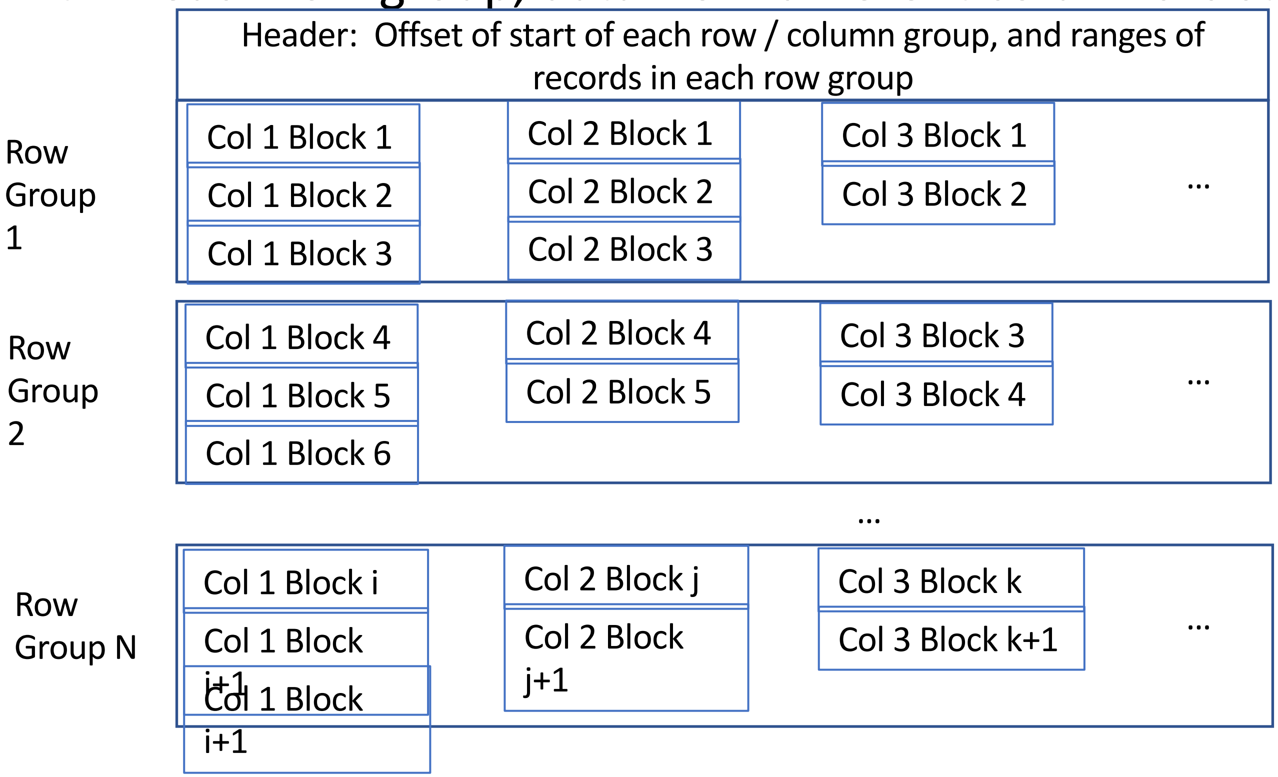
- One popular open-source option: Parquet

Efficient Data Loading: Parquet

- Parquet is column-oriented file format that is MUCH more efficient than CSV for storing tabular data
- Vs CSV, Parquet is stored in binary representation
  - Uses less space
  - Doesn’t require conversion from strings to internal types
  - Doesn’t require parsing or error detection
  - Column-oriented, making access to subsets of columns much faster

Parquet Format

- Data is partitioned sets of rows, called “row groups”
- Within each row group, data from different columns is stored separately



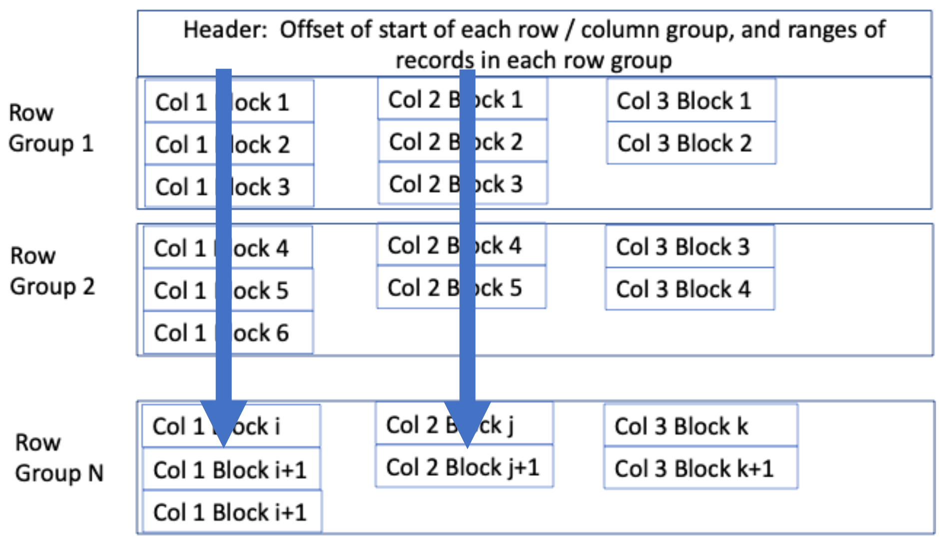
Using header, can efficiently read any subset of columns or rows without scanning whole file (unlike CSV)

Within a row group, data for each column is stored together

Predicate Pushdown w/ Parquet & Pandas

```
pd.read_parquet('file.pq', columns=['Col 1', 'Col 2'])
```

- Only reads col1 and col2 from disk
- For a wide dataset saves a ton of I/O



Performance Measurement

- Compare reading CSV to parquet to just columns we need

```
t = time.perf_counter()
df = pd.read_csv("FARS2019NationalCSV/Person.CSV", encoding = "ISO-8859-1")
print(f"csv elapsed = {time.perf_counter() - t:.3} seconds")

t = time.perf_counter()
df = pd.read_parquet("2019.pq")
print(f"parquet elapsed = {time.perf_counter() - t:.3} seconds")

t = time.perf_counter()
df = pd.read_parquet("2019.pq", columns = ['STATE','ST_CASE','DRINKING','PER_TYP'])
print(f"parquet subset elapsed = {time.perf_counter() - t:.3} seconds")
```

```
csv elapsed = 1.18 seconds
parquet elapsed = 0.338 seconds
parquet subset elapsed = 0.025 seconds
```

47x speedup

When to Use Parquet?

- Will always be more efficient than CSV
- Converting from Parquet to CSV takes time, so only makes sense to do so if working repeatedly with a file
- Parquet requires a library to access/read it, whereas many tools can work with CSV
- Because CSV is text, it can have mixed types in columns, or other inconsistencies
  - May be useful sometimes, but also very annoying!
  - Parquet does not support mixed types in a column

Summary

- Column oriented databases are a different way to “linearize” data to disk than the row-oriented representation we have studied
- A good fit for “warehousing” workloads that mostly read many records of a few tables
- C-Store system implements many additional ideas:
  - “Late materialization” execution
  - Column-specific compression and direct execution on compressed data
  - Read/write optimized stores
- Ideas have found their way into many modern systems and libraries, e.g., Parquet