Columnar Data in 2024:
The Future of Efficient Data Analytics

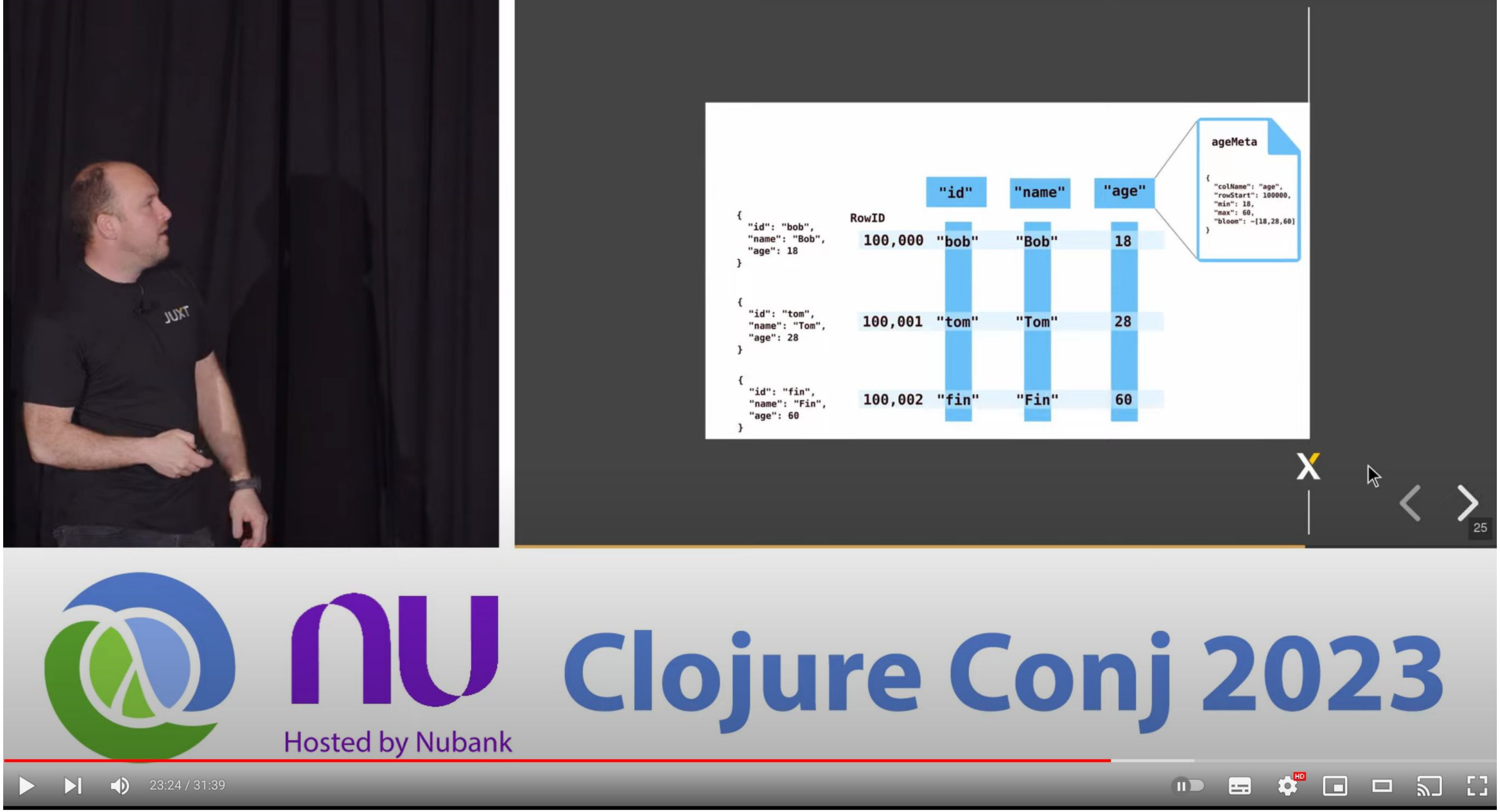
Jeremy Taylor, Head of Product
jdt@juxt.pro
@refset

JUXT

a glacier with ancient frozen columns of binary data visible within

About Me

Ex-IBM
Head of Product, xtdb.com
@refset



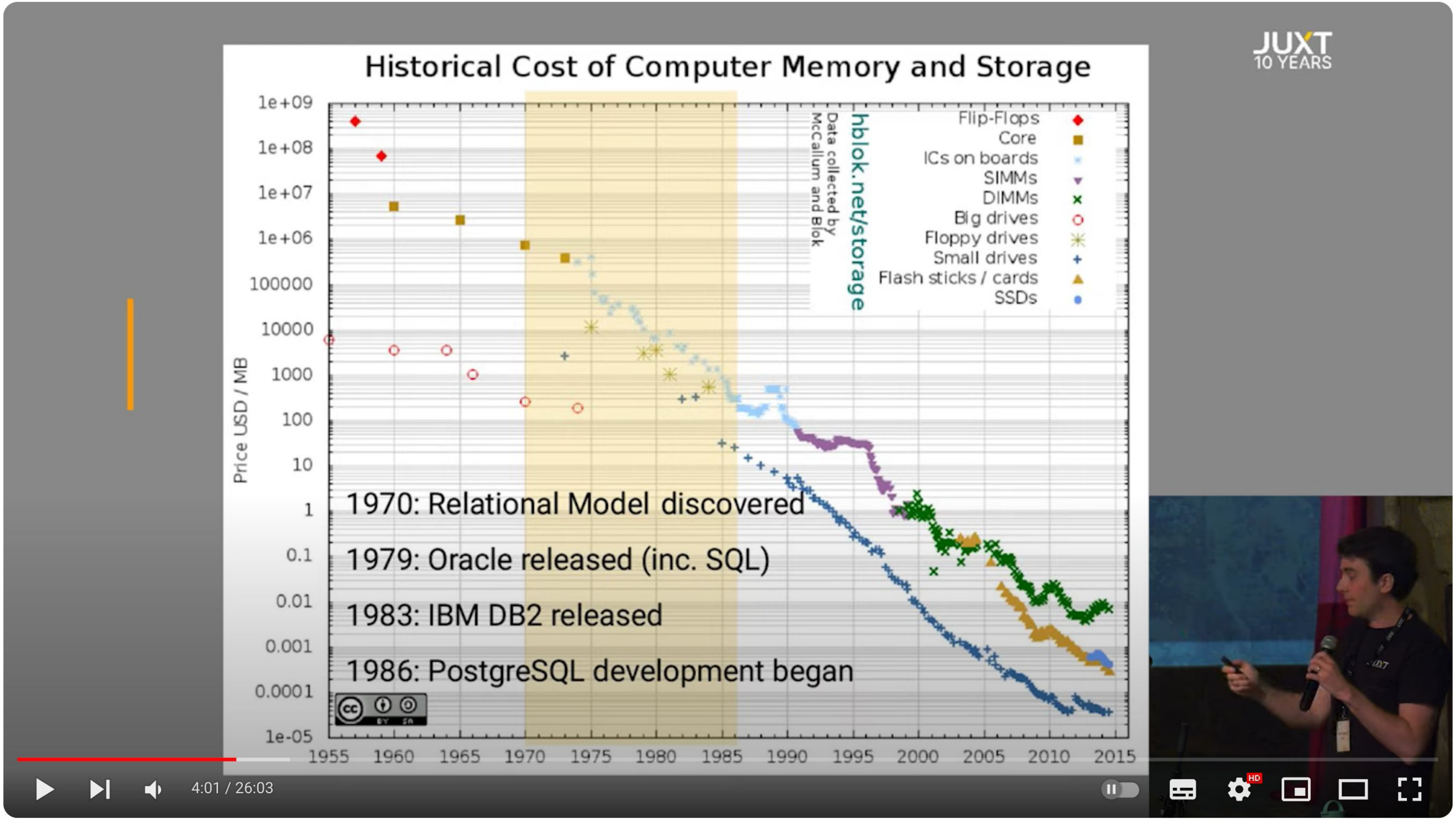
"State of XTDB" by Jon Pither

ClojureTV
28.2K subscribers
Subscribed

44 Share Save

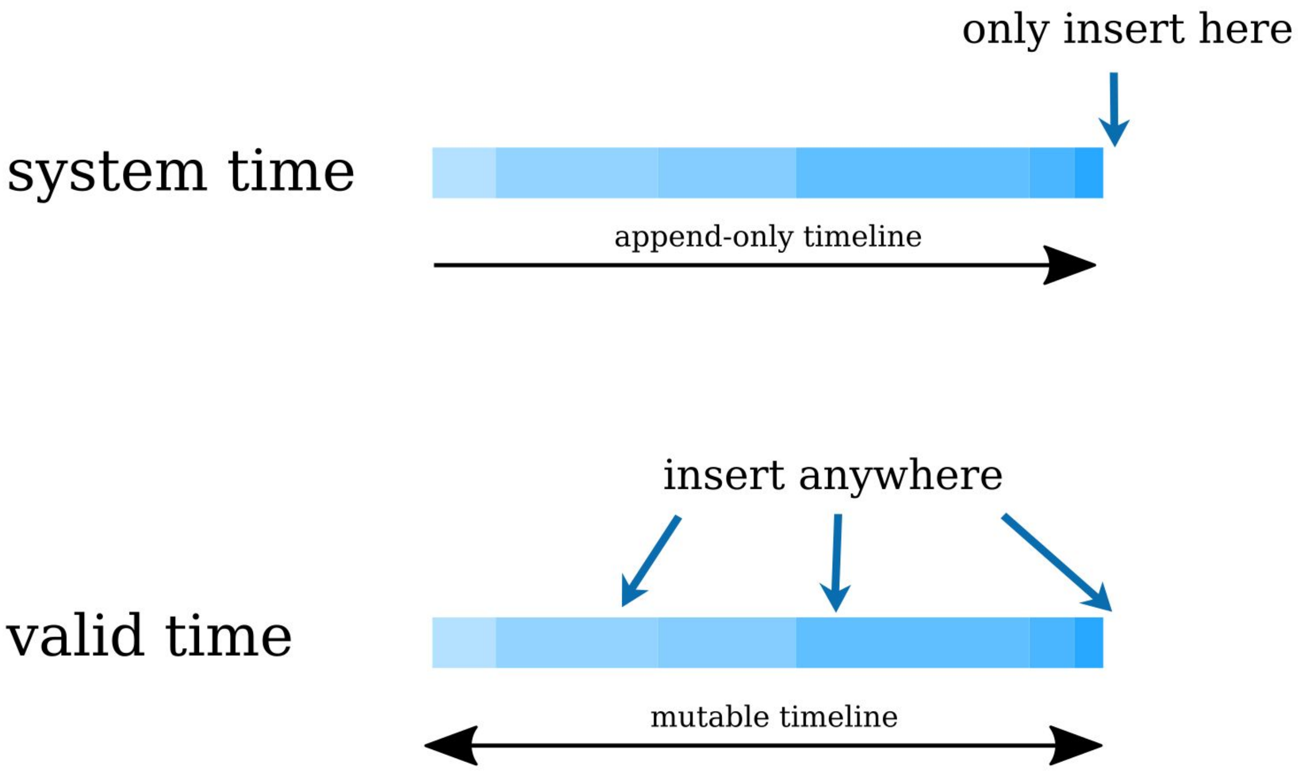
1.3K views 6 months ago DURHAM

https://www.youtube.com/watch?v=gQV-XrkJj2o



"UPDATE Considered Harmful" by Jeremy Taylor

https://www.youtube.com/watch?v=JxMz-tyicgo


only insert here
system time
append-only timeline
insert anywhere
valid time
mutable timeline

Today's Topics

1. Columnar data 101
2. Context & trends
3. Modern analytic systems
4. R&D

JUXT

RELATIONAL MODEL

A relation is an unordered set that contain the relationship of attributes that represent entities.

A tuple is a set of attribute values (also known as its domain) in the relation.

→ Values are (normally) atomic/scalar.

→ The special value **NULL** is a member of every domain (if allowed).

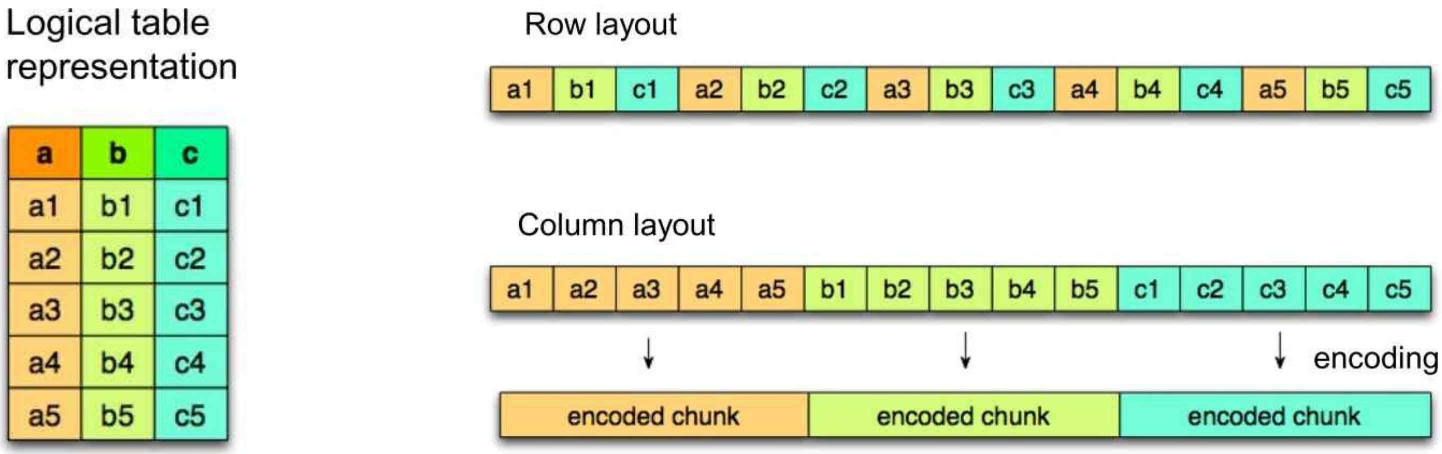
`Artist(name, year, country)`

name	year	country
Wu-Tang Clan	1992	USA
Notorious BIG	1992	USA
GZA	1990	USA

n-ary Relation

=

Table with *n* columns


Logical table representation
a b c
a1 b1 c1
a2 b2 c2
a3 b3 c3
a4 b4 c4
a5 b5 c5
Row layout
a1 b1 c1 a2 b2 c2 a3 b3 c3 a4 b4 c4 a5 b5 c5
Column layout
a1 a2 a3 a4 a5 b1 b2 b3 b4 b5 c1 c2 c3 c4 c5
encoding
encoded chunk
encoded chunk
encoded chunk

	session_id	timestamp	source_ip
Row 1	1331246660	3/8/2012 2:44PM	99.155.155.225
Row 2	1331246351	3/8/2012 2:38PM	65.87.165.114
Row 3	1331244570	3/8/2012 2:09PM	71.10.106.181
Row 4	1331261196	3/8/2012 6:46PM	76.102.156.138

Row-oriented Memory Buffer

Row 1	1331246660
	3/8/2012 2:44PM
	99.155.155.225
Row 2	1331246351
	3/8/2012 2:38PM
	65.87.165.114
Row 3	1331244570
	3/8/2012 2:09PM
	71.10.106.181
Row 4	1331261196
	3/8/2012 6:46PM
	76.102.156.138

Column-oriented Memory Buffer

session_id	1331246660
	1331246351
	1331244570
	1331261196
timestamp	3/8/2012 2:44PM
	3/8/2012 2:38PM
	3/8/2012 2:09PM
	3/8/2012 6:46PM
source_ip	99.155.155.225
	65.87.165.114
	71.10.106.181
	76.102.156.138

The idea behind *column-oriented storage* is simple: don’t store all the values from one row together, but store all the values from each *column* together instead.

If each column is stored in a separate file, a query only needs to read and parse those columns that are used in that query, which can save a lot of work.

Columnar data storage example

- Suppose we have a 1TB table with 100 columns.
- We have a query that requires 5 columns of the table.
  - Row-store:
    Read entire 1TB of data from disk at 100MB/s ≈ 3 hours
  - Columnar storage:
    Read 5 columns (50GB) from disk ≈ 8 minutes

https://www.youtube.com/watch?v=cBWlTLTMwfQ

Compression

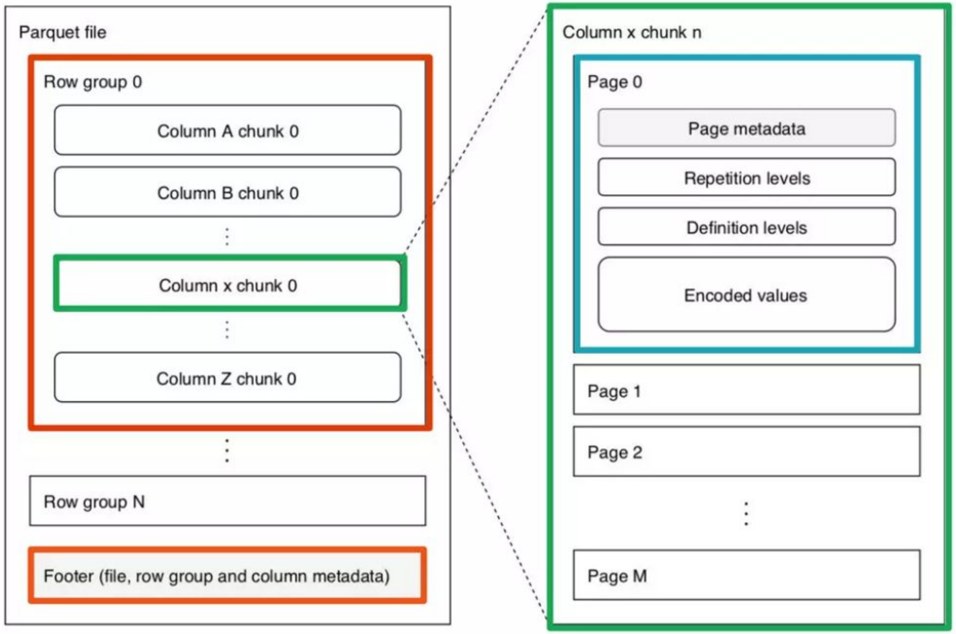
- We have a query that requires 5 columns of the table.
  - No compression:
    Read 5 columns (50GB) from disk ≈ 8 minutes
  - Compression:
    Read 5 compressed columns (5x -> 10GB) from disk ≈ 1:40 minutes

Parquet

1) Columnar layout
2) On-disk compression (e.g. Run-Length Encoding)
3) ~Ideal cold storage

Parquet: data organization

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



https://www.slideshare.net/databricks/the-parquet-format-and-performance-optimization-opportunities

Optimization: predicate pushdown

```
SELECT * FROM table WHERE x > 5

Row-group 0: x: [min: 0, max: 9]
Row-group 1: x: [min: 3, max: 7]
Row-group 2: x: [min: 1, max: 4]
...
```

- Leverage min/max statistics

https://www.slideshare.net/databricks/the-parquet-format-and-performance-optimization-opportunities

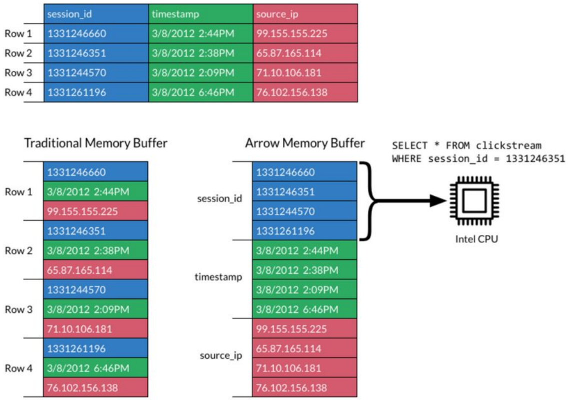
Apache Arrow Overview

Apache Arrow is a software development platform for building high performance applications that process and transport large data sets. It is designed to both improve the performance of analytical algorithms and the efficiency of moving data from one system or programming language to another.

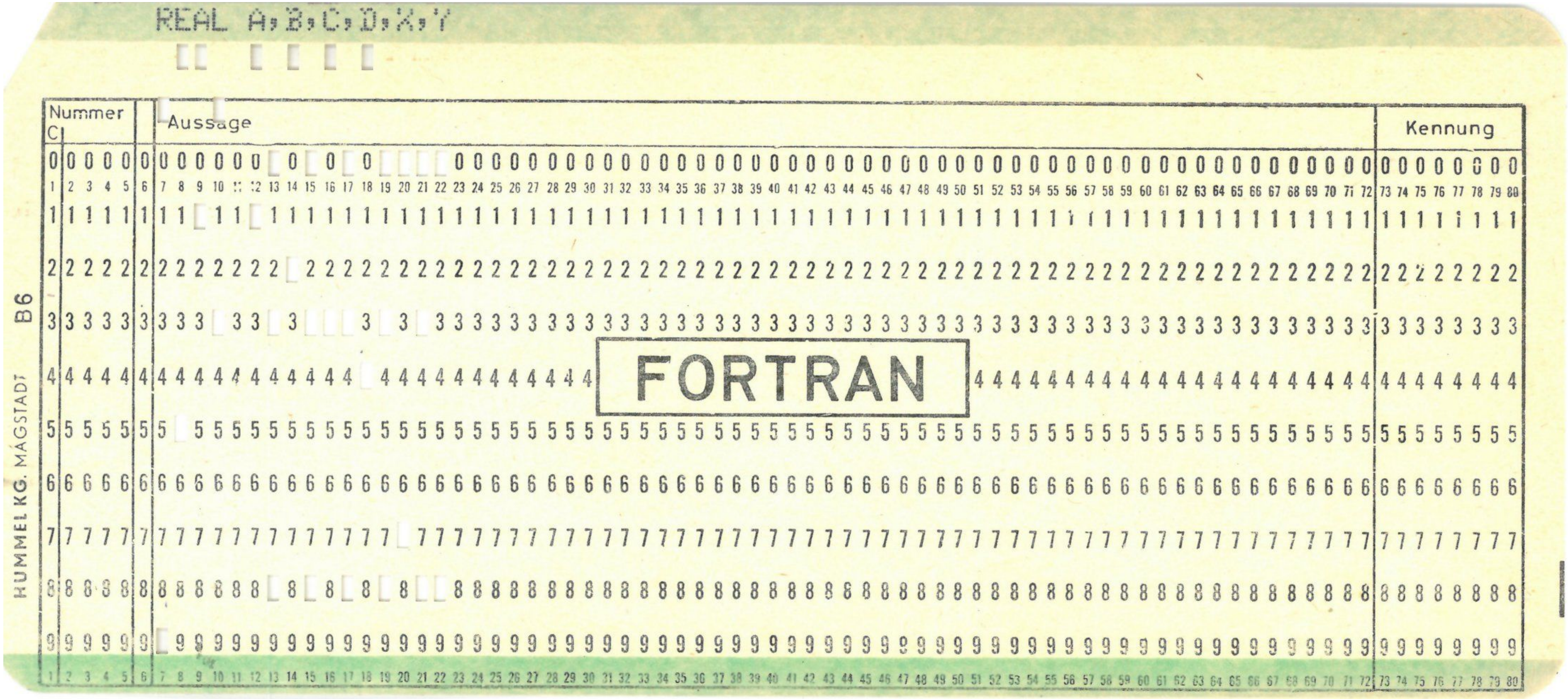
A critical component of Apache Arrow is its **in-memory columnar format**, a standardized, language-agnostic specification for representing structured, table-like datasets in-memory. This data format has a rich data type system (included nested and user-defined data types) designed to support the needs of analytic database systems, data frame libraries, and more.

Columnar is Fast

The Apache Arrow format allows computational routines and execution engines to maximize their efficiency when scanning and iterating large chunks of data. In particular, the contiguous columnar layout enables vectorization using the latest SIMD (Single Instruction, Multiple Data) operations included in modern processors.



Context & Trends


REAL A,B,C,D,X,Y
Nummer
C
Aussage
Kennung
FORTRAN
HUMMEL KG. MAGSTADT
B6

https://www.youtube.com/watch?v=NMWzgy8FsKs

FORTRAN

"our primary objective was to permit people to concentrate on the essence of their problems and eliminate preoccupation with the mechanics of the computer"

- Irv Ziller, The Beginnings of Fortran

https://www.youtube.com/watch?v=KohboWwrsXg

Passing arrays between languages

Fortran stores array elements in ascending storage units in column-major order. C stores array elements in row-major order. Fortran array indexes start at 1, while C array indexes start at 0.

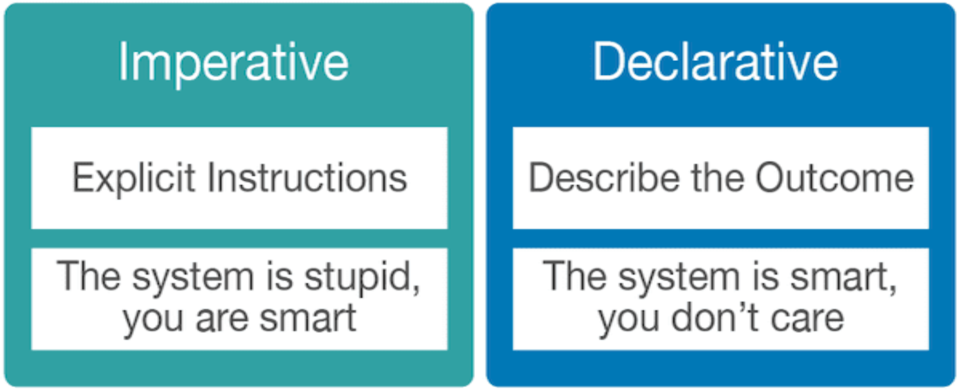
XL Fortran: Optimization and Programming Guide
https://www.ibm.com/docs/en/SSGH4D_15.1.3/com.ibm.compilers.aix.doc/proguide.pdf

HOT long vectorization

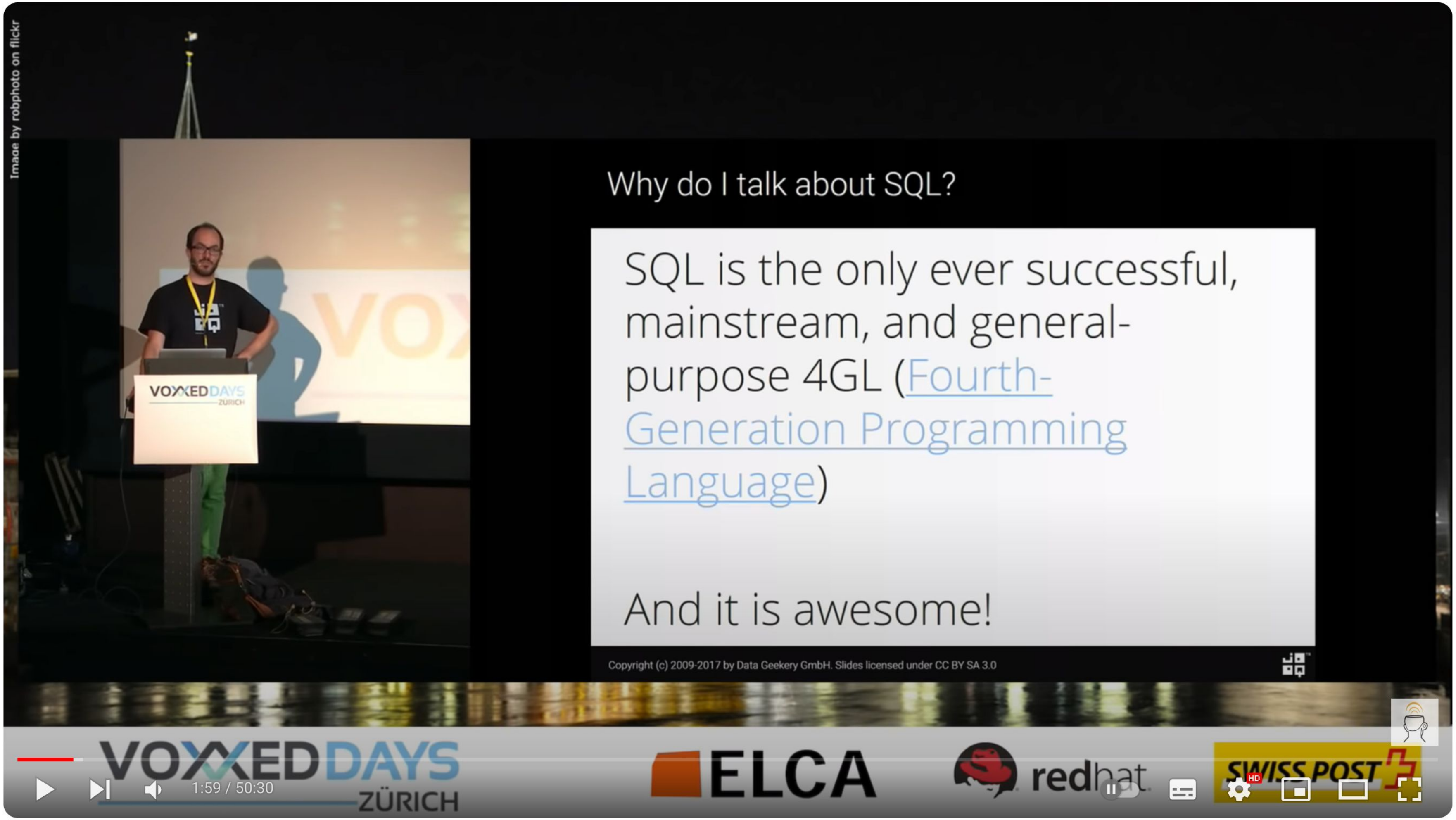
When you specify any of the following:

- **-O4** and higher
- **-qhot** with **-qnostrict**

you enable **-qhot=vector** by default. Specifying **-qnostrict** with optimizations other than **-O4** and **-O5** ensures that the compiler looks for long vectorization opportunities. This can optimize loops in source code for operations on array data by ensuring that operations run in parallel where applicable. The compiler uses standard machine registers for these transformations and does not restrict vector data size; supporting both single- and double-precision floating-point vectorization. Often, HOT vectorization involves transformations of loop calculations into calls to specialized mathematical routines supplied with the compiler such as the Mathematical Acceleration Subsystem (MASS) libraries. These mathematical routines use algorithms that calculate results more efficiently than executing the original loop code.

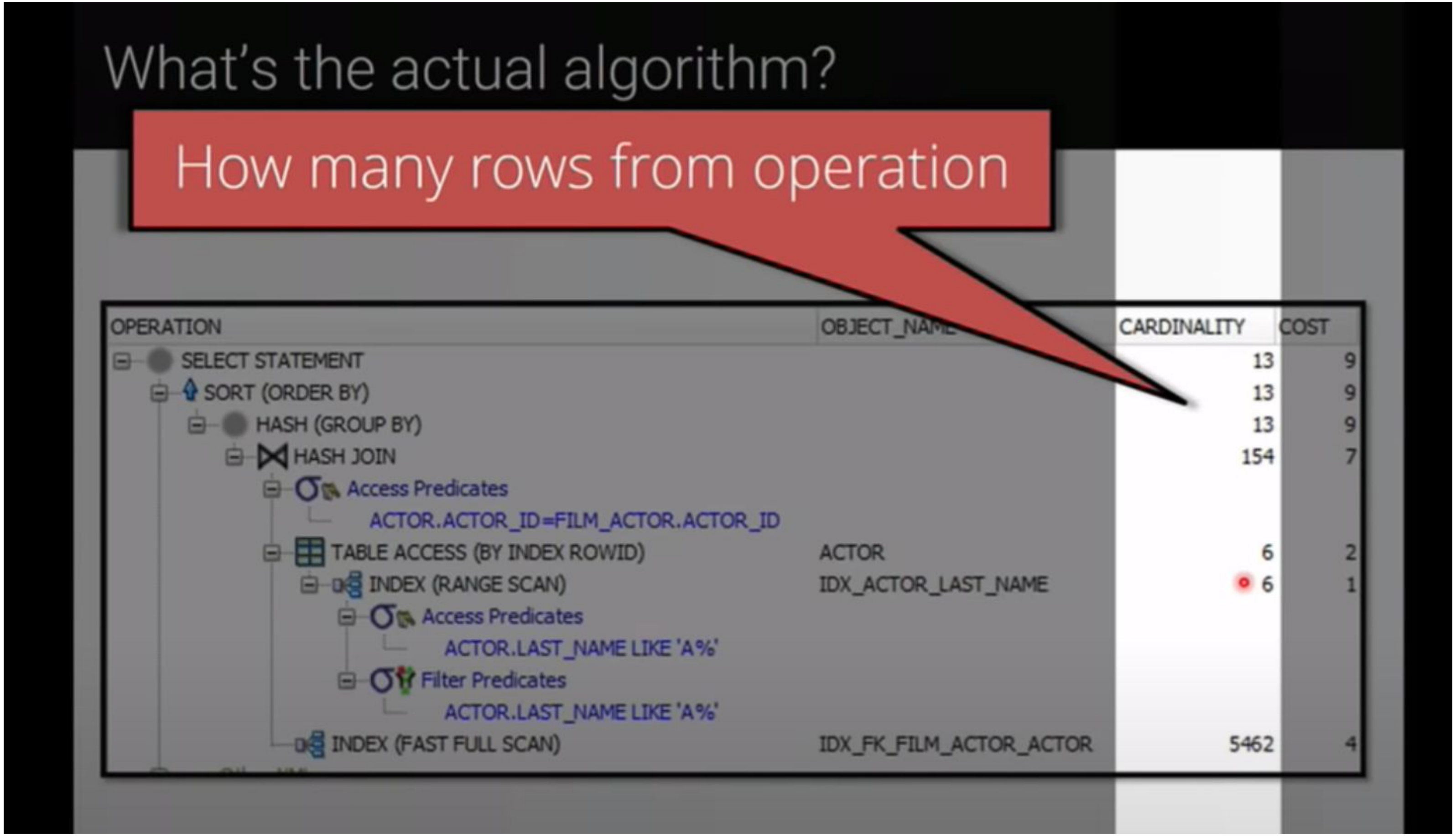


https://www.copebit.ch/en/how-declarative-and-imperative-styles-differ-in-infrastructure-as-code/

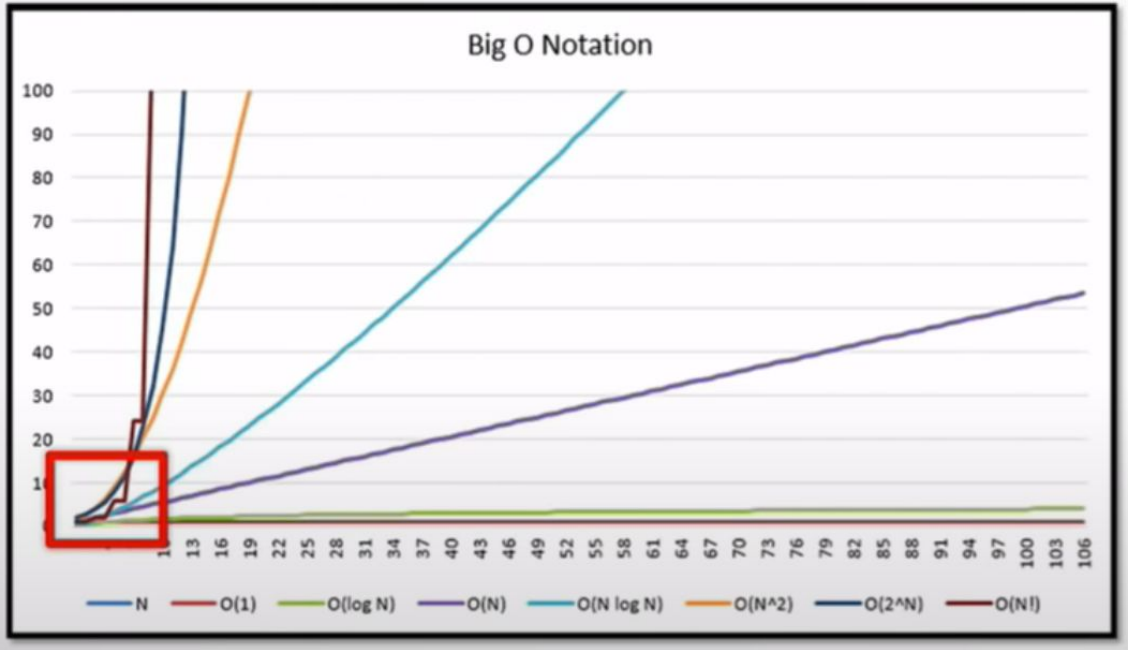


How Modern SQL Databases Come up with Algorithms that You Would Have Never Dreamed Of by Lukas Eder

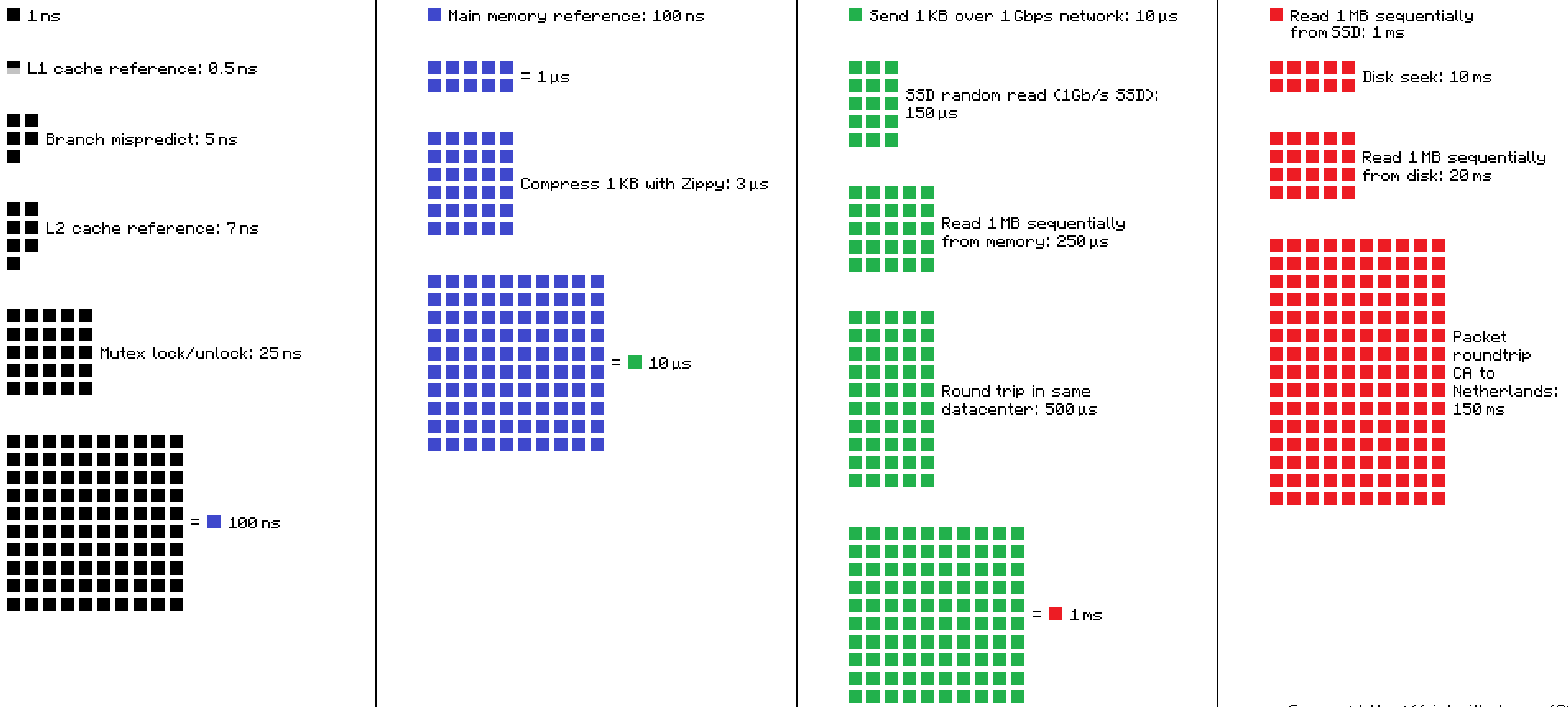
https://www.youtube.com/watch?v=wTPGW1PNy_Y


What's the actual algorithm?
How many rows from operation
OPERATION
OBJECT_NAME
CARDINALITY
COST
SELECT STATEMENT 13 9
SORT (ORDER BY) 13 9
HASH (GROUP BY) 13 9
HASH JOIN 154 7
Access Predicates
ACTOR.ACTOR_ID=FILM_ACTOR.ACTOR_ID
TABLE ACCESS (BY INDEX ROWID) ACTOR 6 2
INDEX (RANGE SCAN) IDX_ACTOR_LAST_NAME 6 1
Access Predicates
ACTOR.LAST_NAME LIKE 'A%'
Filter Predicates
ACTOR.LAST_NAME LIKE 'A%'
INDEX (FAST FULL SCAN) IDX_FK_FILM_ACTOR_ACTOR 5462 4

Your estimate / dev environment is here



Latency Numbers Every Programmer Should Know



Source: https://gist.github.com/2841832

https://gist.github.com/hellerbarde/2843375

Lets multiply all these durations by a billion:

Magnitudes:

Minute:

```
L1 cache reference                    0.5 s         One heart beat (0.5 s)
Branch mispredict                     5 s           Yawn
L2 cache reference                    7 s           Long yawn
Mutex lock/unlock                     25 s          Making a coffee
```

Hour:

```
Main memory reference                 100 s         Brushing your teeth
Compress 1K bytes with Zippy          50 min        One episode of a TV show (including ad breaks)
```

Day:

```
Send 2K bytes over 1 Gbps network     5.5 hr        From lunch to end of work day
```

Week

```
SSD random read                       1.7 days      A normal weekend
Read 1 MB sequentially from memory    2.9 days      A long weekend
Round trip within same datacenter     5.8 days      A medium vacation
Read 1 MB sequentially from SSD      11.6 days      Waiting for almost 2 weeks for a delivery
```

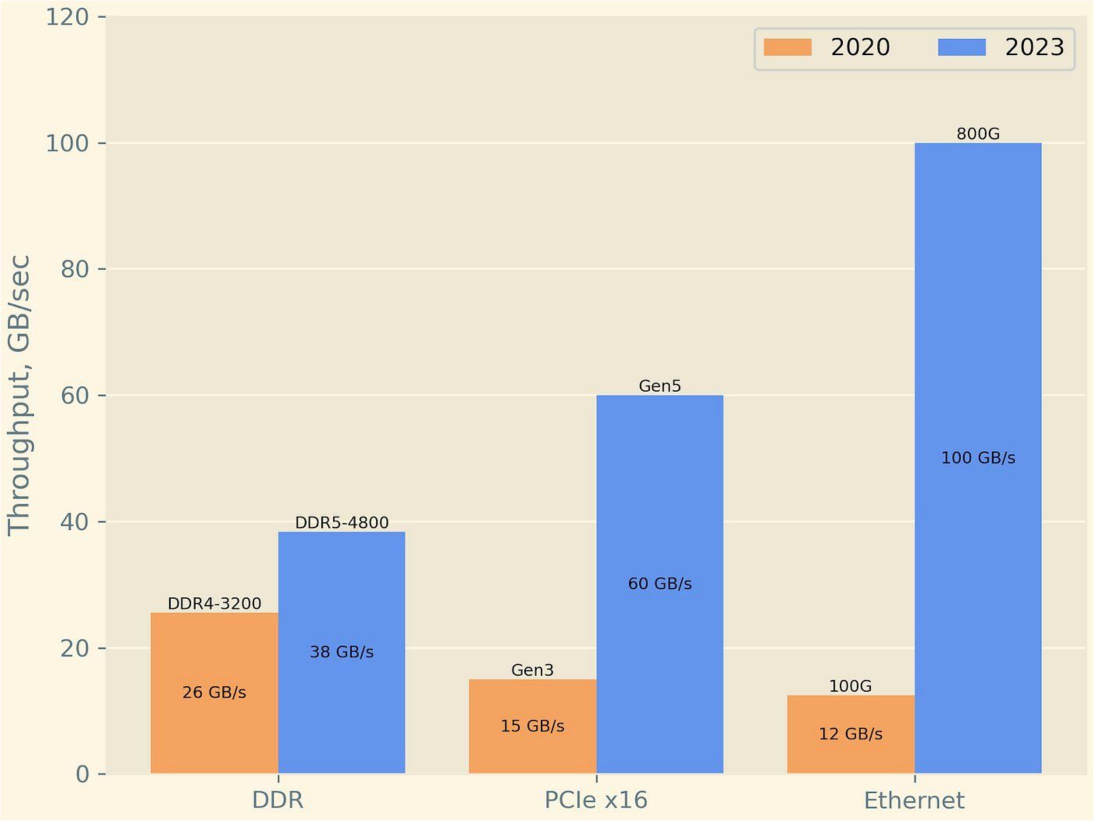
Year

```
Disk seek                             16.5 weeks    A semester in university
Read 1 MB sequentially from disk      7.8 months    Almost producing a new human being
The above 2 together                  1 year
```

Decade

```
Send packet CA->Netherlands->CA       4.8 years     Average time it takes to complete a bachelor's degree
```

The ebb and flow of relative bandwidth...



https://blog.enfabrica.net/the-next-step-in-high-performance-distributed-computing-systems-4f98f13064ac

The Three Dimensions of Big Data Management

- **Data Gravity** – costs of moving
- **Data Residency** – legal implications
- **Data Latency** – the hardest technical challenge

https://intellyx.com/2022/09/19/gravity-residency-and-latency-balancing-the-three-dimensions-of-big-data/

Mechanical Sympathy

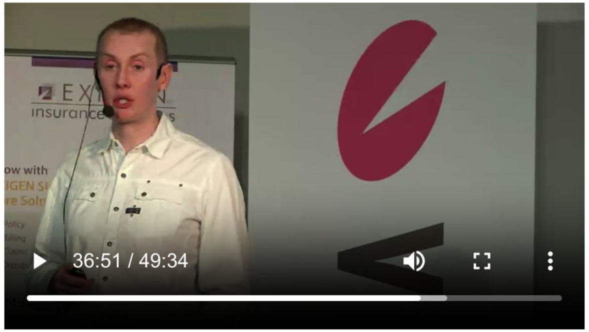
- **Mechanical sympathy is when you use a tool or system with an understanding of how it operates best**
  - You don't need to be a hardware engineer
  - You do need to understand how the hardware works and take that into consideration when you design software

https://dzone.com/articles/mechanical-sympathy

Mechanical Sympathy

LIKE 4

View Presentation Speed: 1X 1.25X 1.5X 2X



Download MP3 SLIDES 49:34

Summary

Martin Thompson ponders if there is a mechanical sympathy between developers and computers, and how to balance elegant design with the application of science in the development of modern software.

https://www.infoq.com/presentations/mechanical-sympathy/

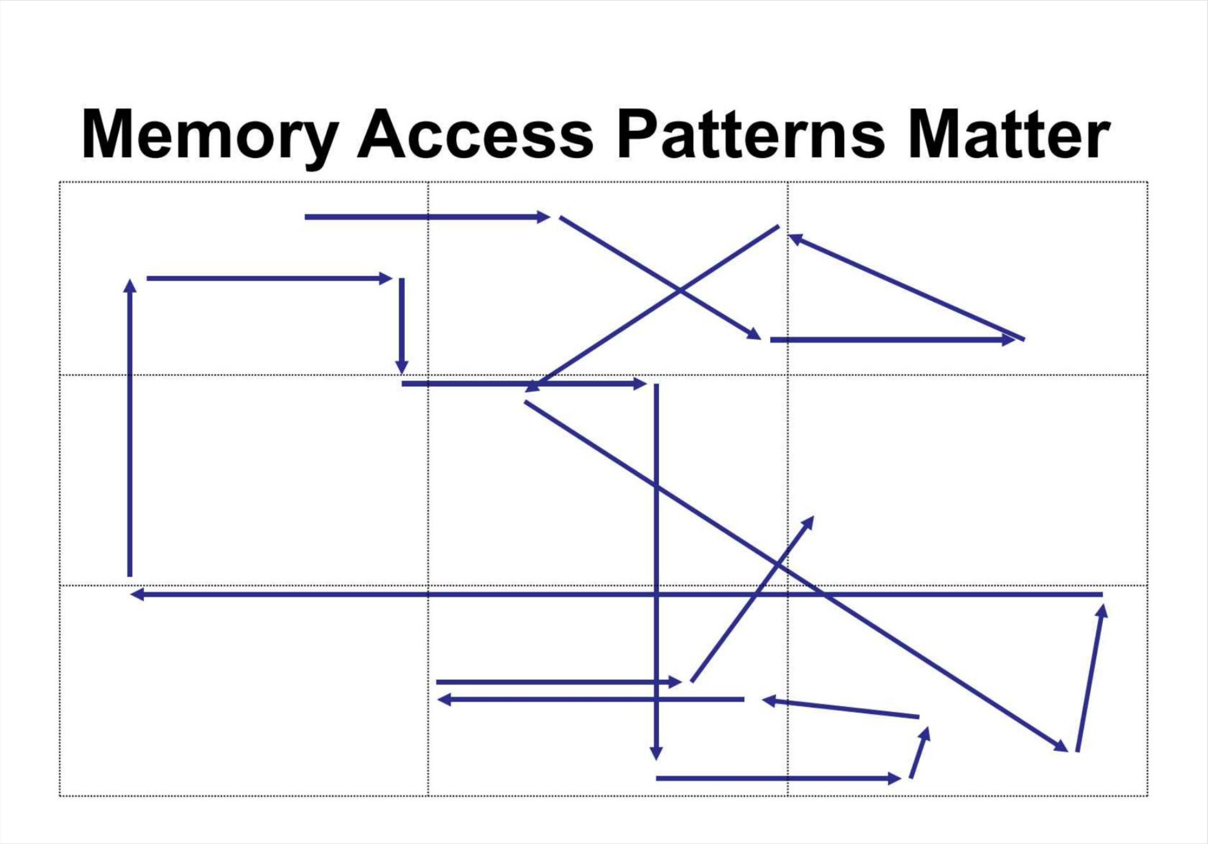
Mechanical Sympathy

LIKE 4

View Presentation

Speed: 1X 1.25X 1.5X 2X

Download MP3 SLIDES 49:34



Summary

Martin Thompson ponders if there is a mechanical sympathy between developers and computers, and how to balance elegant design with the application of science in the development of modern software.

Mechanical Sympathy in Software Design

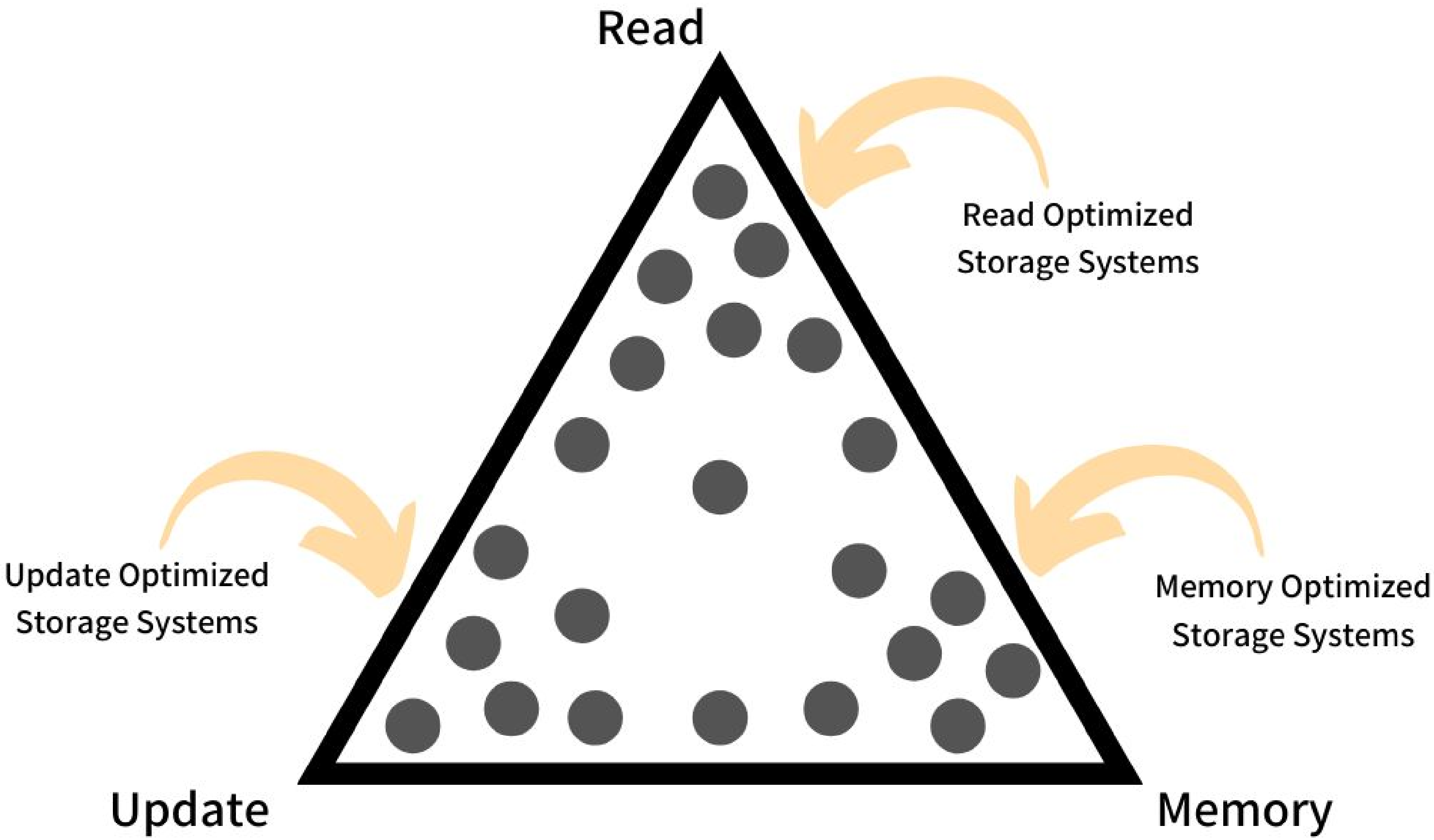
- **Keys to performance: minimize instructions, minimize data**
  - Do the most work in the fewest instructions
  - Reduce the data being shunted around
- You achieve this by modeling the problem domain and eliminating non-essential complexity.

Mechanical Sympathy in Main Memory

- Bandwidth has exploded while latencies are the ~same
- To hide latency CPUs use evermore complex layers of caches
- CPUs hide memory latency using 3 heuristics:
  - **Temporal**: Recent data will likely be required again soon
  - **Spatial**: Adjacent data is likely to be required next
  - **Striding**: Memory access is likely to follow simple patterns

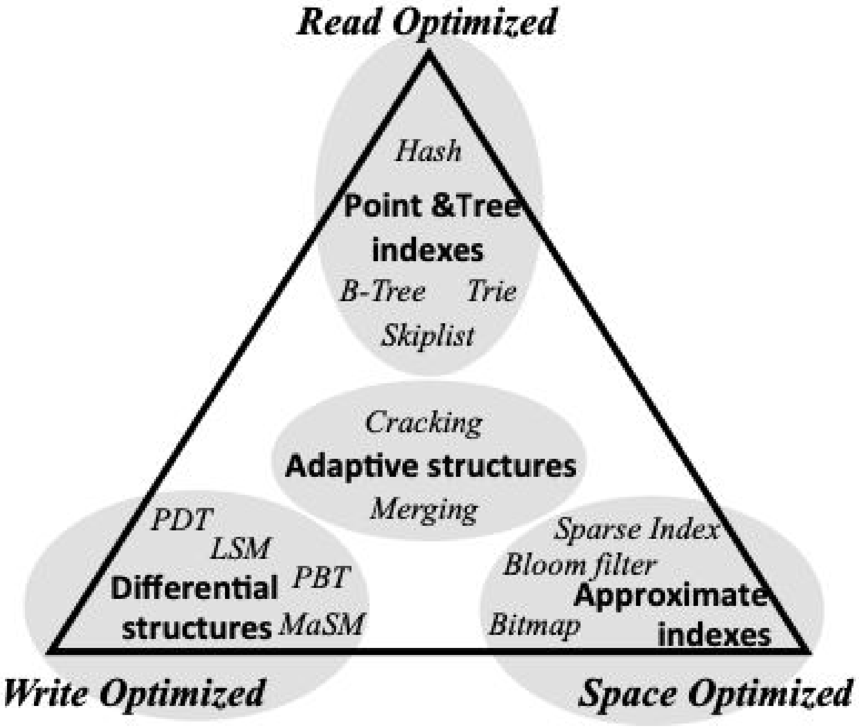
https://mechanical-sympathy.blogspot.com/2012/08/memory-access-patterns-are-important.html

The RUM Conjecture

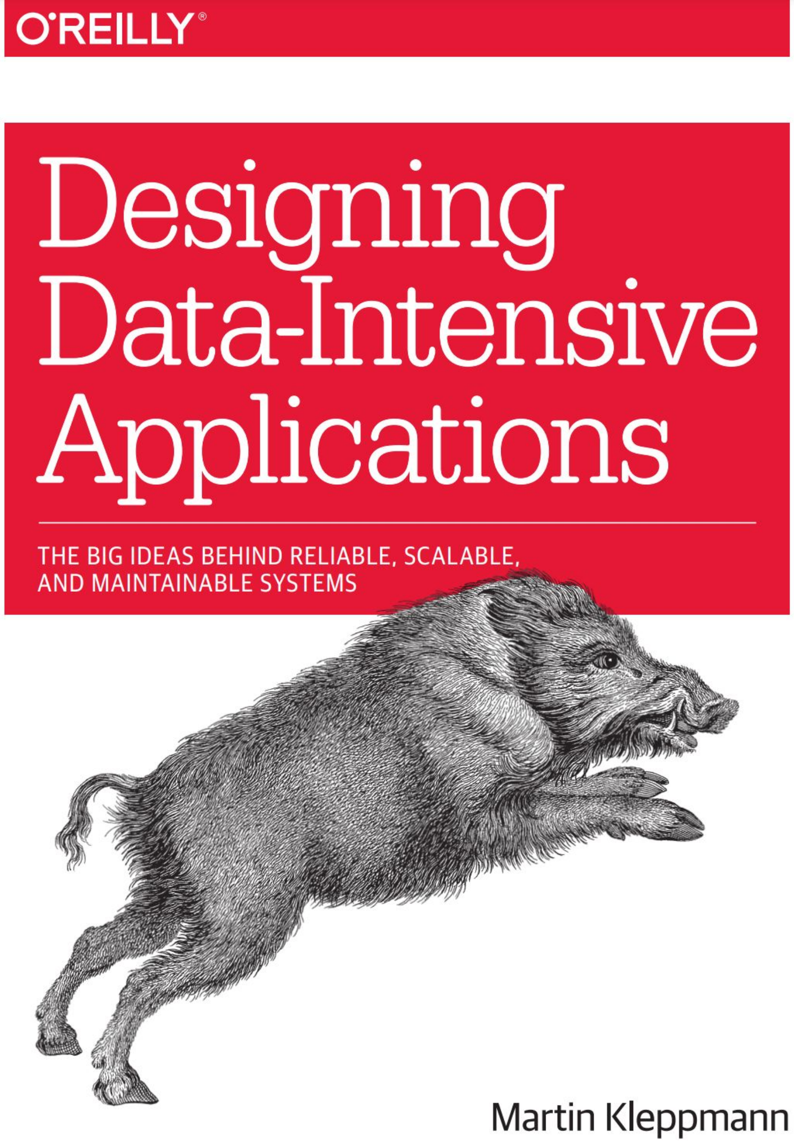


https://medium.com/@arpitbhayani/the-rum-conjecture-bce86c2517e3

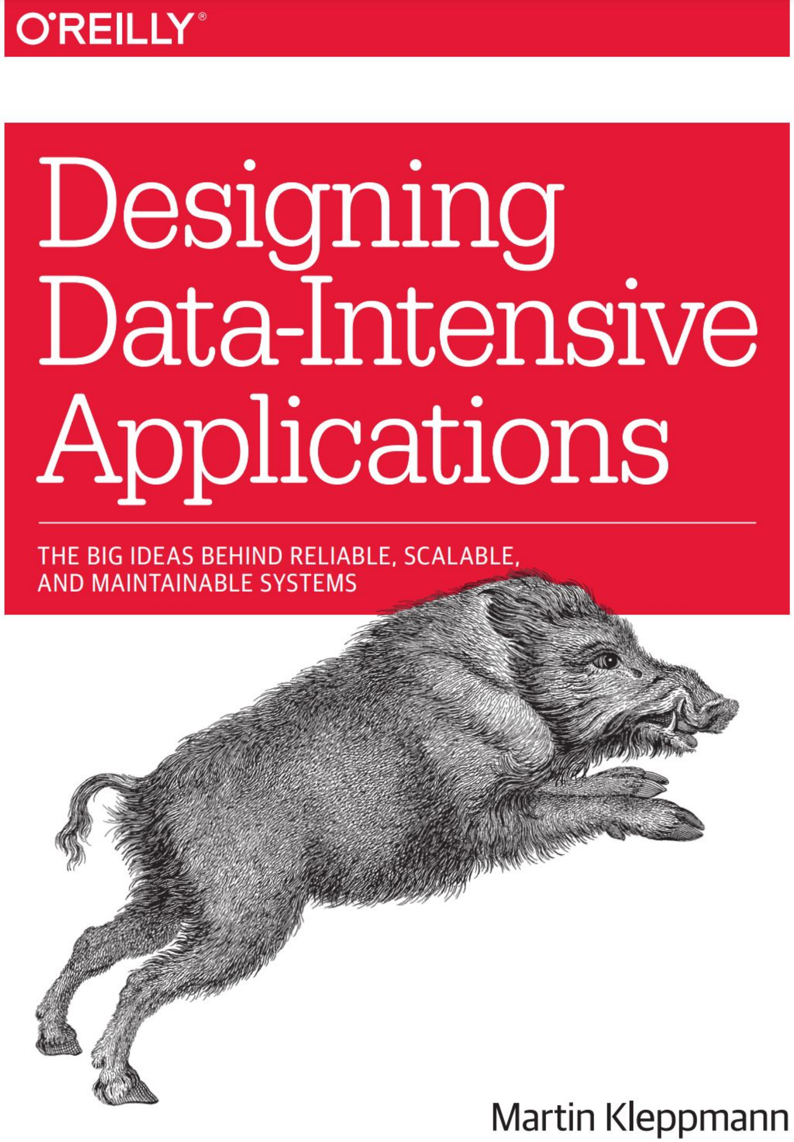
A single algorithm can only minimize two out of: Read / Update / Memory overheads



https://stratos.seas.harvard.edu/files/stratos/files/rum.pdf



https://dataintensive.net/



...as opposed to "Compute-Intensive"

Key qualities:

- Reliability (fault-tolerance)
- Scalability (response to load)
- Maintainability (simplicity)

Table 3-1. Comparing characteristics of transaction processing versus analytic systems

Property	Transaction processing systems (OLTP)	Analytic systems (OLAP)
Main read pattern	Small number of records per query, fetched by key	Aggregate over large number of records
Main write pattern	Random-access, low-latency writes from user input	Bulk import (ETL) or event stream
Primarily used by	End user/customer, via web application	Internal analyst, for decision support
What data represents	Latest state of data (current point in time)	History of events that happened over time
Dataset size	Gigabytes to terabytes	Terabytes to petabytes

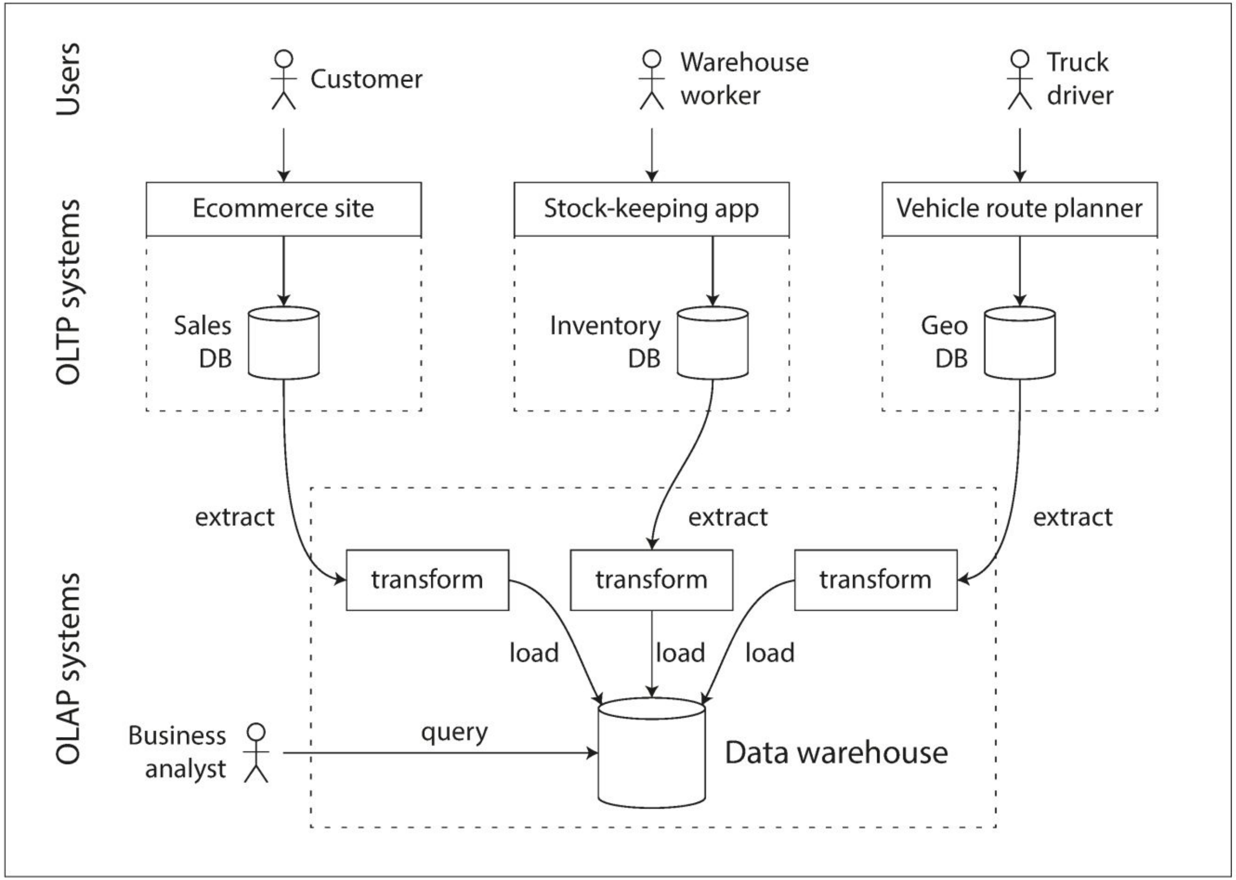


Figure 3-8. Simplified outline of ETL into a data warehouse.

"In a typical data warehouse, tables are often very wide: ***fact tables*** often have **over 100 columns**, sometimes several hundred" fact_sales table

date_key	product_sk	store_sk	promotion_sk	customer_sk	quantity	net_price	discount_price
140102	69	4	NULL	NULL	1	13.99	13.99
140102	69	5	19	NULL	3	14.99	9.99
140102	69	5	NULL	191	1	14.99	14.99
140102	74	3	23	202	5	0.99	0.89
140103	31	2	NULL	NULL	1	2.49	2.49
140103	31	3	NULL	NULL	3	14.99	9.99
140103	31	3	21	123	1	49.99	39.99
140103	31	8	NULL	233	1	0.99	0.99

Columnar storage layout:

date_key file contents:	140102, 140102, 140102, 140102, 140103, 140103, 140103, 140103
product_sk file contents:	69, 69, 69, 74, 31, 31, 31, 31
store_sk file contents:	4, 5, 5, 3, 2, 3, 3, 8
promotion_sk file contents:	NULL, 19, NULL, 23, NULL, NULL, 21, NULL
customer_sk file contents:	NULL, NULL, 191, 202, NULL, NULL, 123, 233
quantity file contents:	1, 3, 1, 5, 1, 3, 1, 1
net_price file contents:	13.99, 14.99, 14.99, 0.99, 2.49, 14.99, 49.99, 0.99
discount_price file contents:	13.99, 9.99, 14.99, 0.89, 2.49, 9.99, 39.99, 0.99

Figure 3-10. Storing relational data by column, rather than by row.

"We can only reconstruct a row because we know that the *kth* item in one column belongs to the same row as the *kth* item in another column."

Column values:

product_sk:	69	69	69	69	74	31	31	31	31	29	30	30	31	31	31	68	69	69

Bitmap for each possible value:

product_sk = 29:	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
product_sk = 30:	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
product_sk = 31:	0	0	0	0	0	1	1	1	1	0	0	0	1	1	1	0	0	0
product_sk = 68:	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
product_sk = 69:	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1
product_sk = 74:	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0

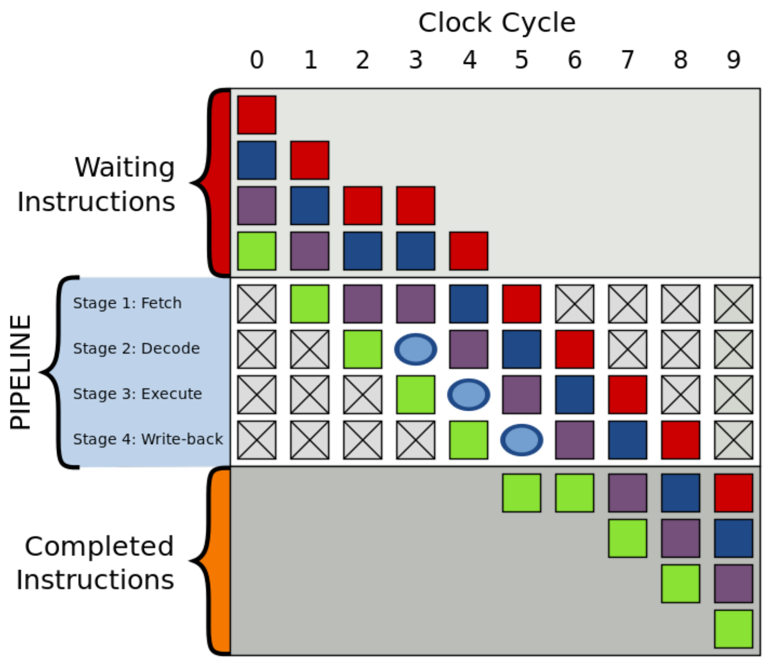
Run-length encoding:

product_sk = 29:	9, 1	(9 zeros, 1 one, rest zeros)
product_sk = 30:	10, 2	(10 zeros, 2 ones, rest zeros)
product_sk = 31:	5, 4, 3, 3	(5 zeros, 4 ones, 3 zeros, 3 ones, rest zeros)
product_sk = 68:	15, 1	(15 zeros, 1 one, rest zeros)
product_sk = 69:	0, 4, 12, 2	(0 zeros, 4 ones, 12 zeros, 2 ones)
product_sk = 74:	4, 1	(4 zeros, 1 one, rest zeros)

Figure 3-11. Compressed, bitmap-indexed storage of a single column.

Scanning Performance ∝ ***Bandwidth***

- CPU Caches < Memory < Disk < Network
- Make efficient use of CPU cycles, keep the CPU fed!
  - Exploit pipelining with “tight loops” (avoid bubbles and branch mispredictions)
  - Use vectorized processing (use L1-cache-sized record batches and avoid decompressing)
  - Hardware parallelism Single instruction, multiple data (SIMD)
- ...avoid latency stalls!



“Next time you are developing an important algorithm, try pondering that a cache-miss is a lost opportunity to have executed ~500 CPU instructions!”
- Martin Thompson

Vectorized query engines

- Two key differences from tuple-at-a-time engines (Postgres etc.)
  - **Column oriented processing** – Write query processing algorithms that operate on columns as long as possible in the execution plan. Refrain from working on tuples till late in the plan (e.g. during projecting result-set back to the user)
  - **Push batches of column vectors through the query plan tree** – Instead of passing around tuple from one operator to another, pass column(s) containing a fixed number of records

Vectorized query processing

- **Better cache locality and efficient utilization of CPU cache** – we can quickly loop through tightly packed values of a column and do the necessary processing – predicate evaluation, arithmetic computations etc. Cache lines are filled with related values (from the same column) as opposed to heterogeneous values from multiple columns in a tuple where some columns may not even be touched by the query
- **Better chance of native optimizations by the compiler** – tight loop based vectorized algorithms are good candidates of automatic optimization by compilers
- **Leverage hardware acceleration** – well aligned column data in densely packed arrays is amenable to acceleration using SIMD instructions. Common operations like FILTER, SUM, MIN, MAX can be accelerated by an order of magnitude by exploiting data-level parallelism of SIMD instructions
- **Directly operate on compressed columnar data** – columnar format allows us to encode column values with lightweight compression algorithms (dictionary encoding, RLE etc) which trade compression ratio for better query performance

Writing columns

- Update-in-place approaches are not possible with compressed columns
- If you want to insert a row in the middle of a table, you most likely have to rewrite all the columns. **As rows are identified by their position within a column, the insertion has to update all columns consistently**
- Query engines often augment column files with LSM-trees
  - All writes first go to an in-memory store
  - When enough writes have accumulated, they are merged with the column files on disk and written to new files in bulk
  - Queries need to examine both the column data on disk and the recent writes in memory, and combine the two
  - The query optimizer hides this distinction from the user, such that inserts, updates, and deletes are immediately reflected in subsequent queries

Sorting of columns

- You can choose the columns by which the table should be sorted, given advance knowledge of common queries
- e.g. **if queries often target date ranges, such as “last month”, sort by date_key first**, then the query optimizer can scan only the rows from the last month, which will be much faster than scanning all rows
- A sorted column is likely to benefit heavily from run-length encoding and other compression

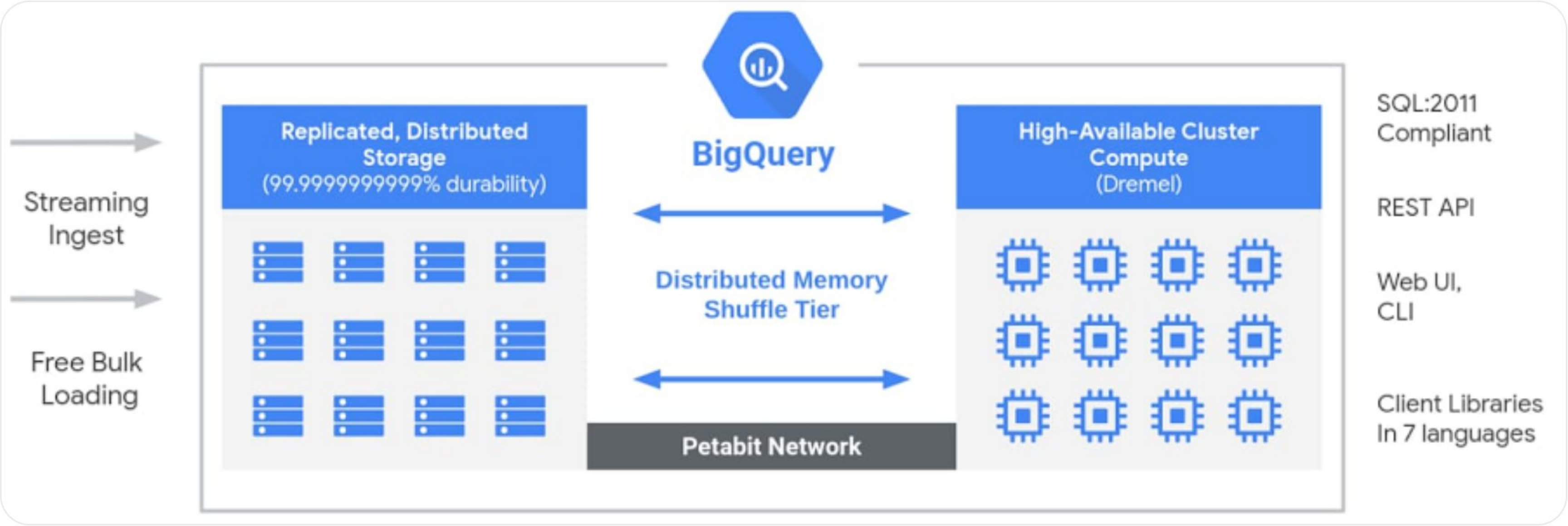
The Rise of Cloud Data Warehouses

- A cloud data warehouse makes no trade-offs from a traditional data warehouse, but extends capabilities and runs on a fully managed service in the cloud
- Cloud data warehousing offers instant scalability to meet changing business requirements and powerful data processing to support complex analytical queries

https://cloud.google.com/learn/what-is-a-data-warehouse

BigQuery Architecture

BigQuery's serverless architecture decouples storage and compute and allows them to scale independently on demand. This structure offers both immense flexibility and cost controls for customers because they don't need to keep their expensive compute resources up and running all the time. This is very different from traditional node-based cloud data warehouse solutions or on-premise massively parallel processing (MPP) systems. This approach also allows customers of any size to bring their data into the data warehouse and start analyzing their data using Standard SQL without worrying about database operations and system engineering.



BigQuery Architecture

snowflake®

WHY SNOWFLAKE · THE DATA CLOUD · SOLUTIONS · RESOURCES · COMPANY

EVERYTHING IS EASIER IN THE DATA CLOUD

Snowflake delivers ease of use, instant elasticity, and lower TCO.

START FOR FREE

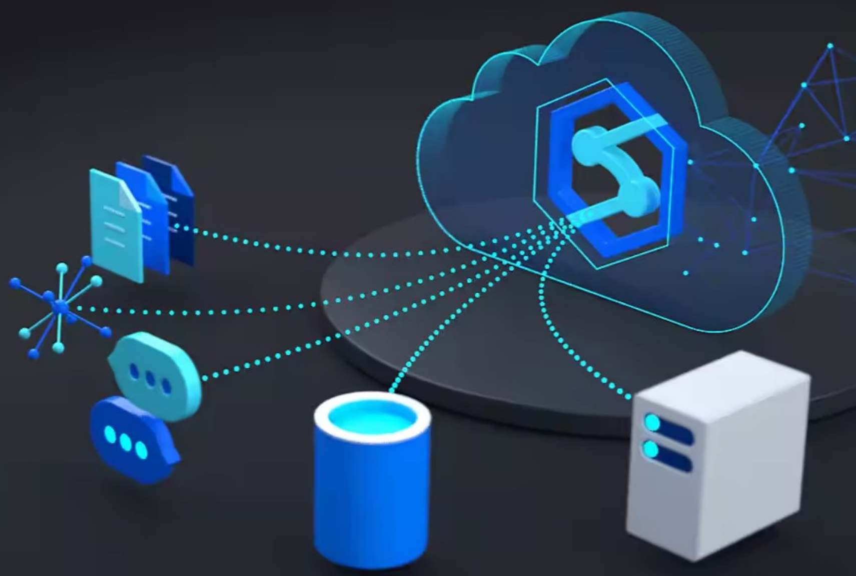
WHY SNOWFLAKE?

Azure Synapse Analytics

Accelerate time to insight across enterprise data warehouses and big data systems.

Try Azure Synapse Analytics free

Create a pay-as-you-go account



Overview Features Security Pricing Get started Customer stories Resources FAQ

Experience a new class of data analytics

Azure Synapse Analytics is an enterprise analytics service that accelerates time to insight across data w
brings together the best of SQL technologies used in enterprise data warehousing, Apache Spark tech
Data Explorer for log and time series analytics.

“HTAP” (Hybrid Transactional/Analytical Processing) – one system to rule them all?

Typical latencies of different database systems

https://medium.com/google-cloud/alloydb-new-kid-on-the-htap-block-188a732fdd35

Azure Synapse Link for Azure Cosmos DB: Near real-time analytics use cases

Article • 10/12/2022 • 7 contributors

Feedback

In this article

Supply chain analytics, forecasting & reporting
Real-time personalization
IOT predictive maintenance
Sample scenario: HTAP for Azure Cosmos DB
Next steps

APPLIES TO: NoSQL MongoDB Gremlin

Azure Synapse Link for Azure Cosmos DB is a cloud native hybrid transactional and analytical processing (HTAP) capability that enables you to run near real-time analytics over operational data. Synapse Link creates a tight seamless integration between Azure Cosmos DB and Azure Synapse Analytics.

You might be curious to understand what industry use cases can leverage this cloud native HTAP capability for near real-time analytics over operational data. Here are three common use cases for Azure Synapse Link for Azure Cosmos DB:

Announcing AlloyDB AI for building generative AI applications with PostgreSQL. Read the blog.

AlloyDB for PostgreSQL

- Benefits
- Key features
- Customers
- What's new

Documentation

Compare features

All features

Pricing

Partners

Take the next step

AlloyDB for PostgreSQL

A fully managed PostgreSQL-compatible database service for your most demanding enterprise workloads. AlloyDB combines the best of Google with PostgreSQL, for superior performance, scale, and availability.

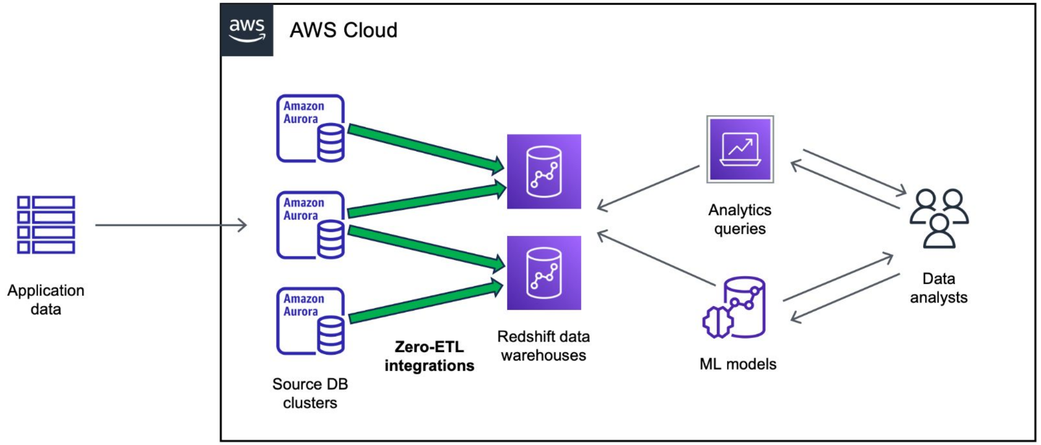
Go to console | Documentation

- ✓ Fully compatible with PostgreSQL, providing flexibility and true portability for your workloads
- ✓ Superior performance, 4x faster than standard PostgreSQL for transactional workloads*
- ✓ Fast, real-time insights, up to 100x faster analytical queries than standard PostgreSQL*
- ✓ AlloyDB AI can help you build a wide range of generative AI applications

Working with zero-ETL integrations
Getting started with zero-ETL integrations
Creating zero-ETL integrations
Adding and querying data
Viewing and monitoring zero-ETL integrations
Deleting zero-ETL integrations
Troubleshooting zero-ETL integrations
Using Aurora Serverless v2
Using Aurora Serverless v1
Using the Data API
Using the query editor
Code examples
Best practices with Aurora
Performing an Aurora proof of concept
Security
Quotas and constraints

To create a zero-ETL integration, you specify an Aurora DB cluster as the *source*, and an Amazon Redshift data warehouse as the *target*. The integration replicates data from the source database into the target data warehouse.

The following diagram illustrates this functionality:



The integration monitors the health of the data pipeline and recovers from issues when possible. You can create integrations from multiple Aurora DB clusters into a single Amazon Redshift namespace, enabling you to derive insights across multiple applications.

For information about pricing for zero-ETL integrations, see Amazon Aurora pricing and Amazon Redshift pricing.

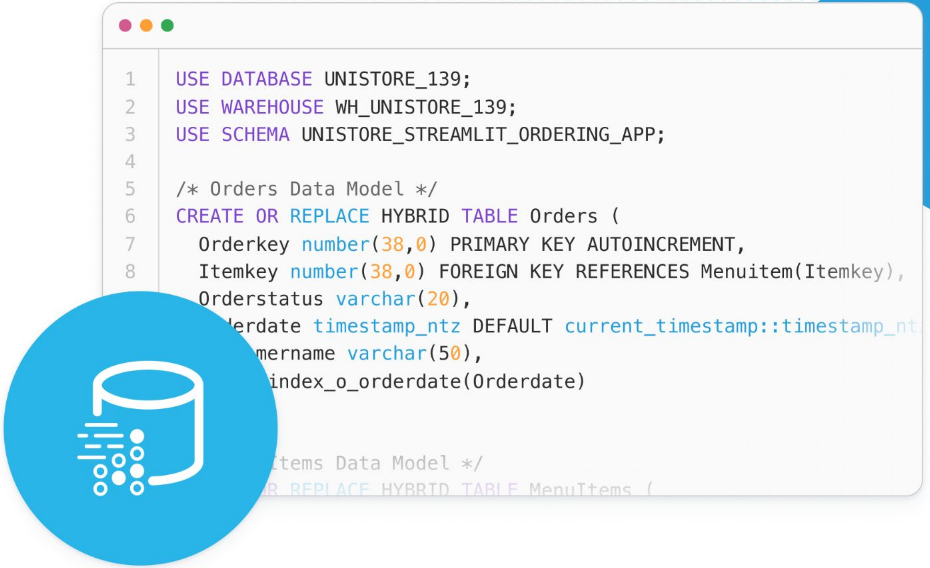
snowflake

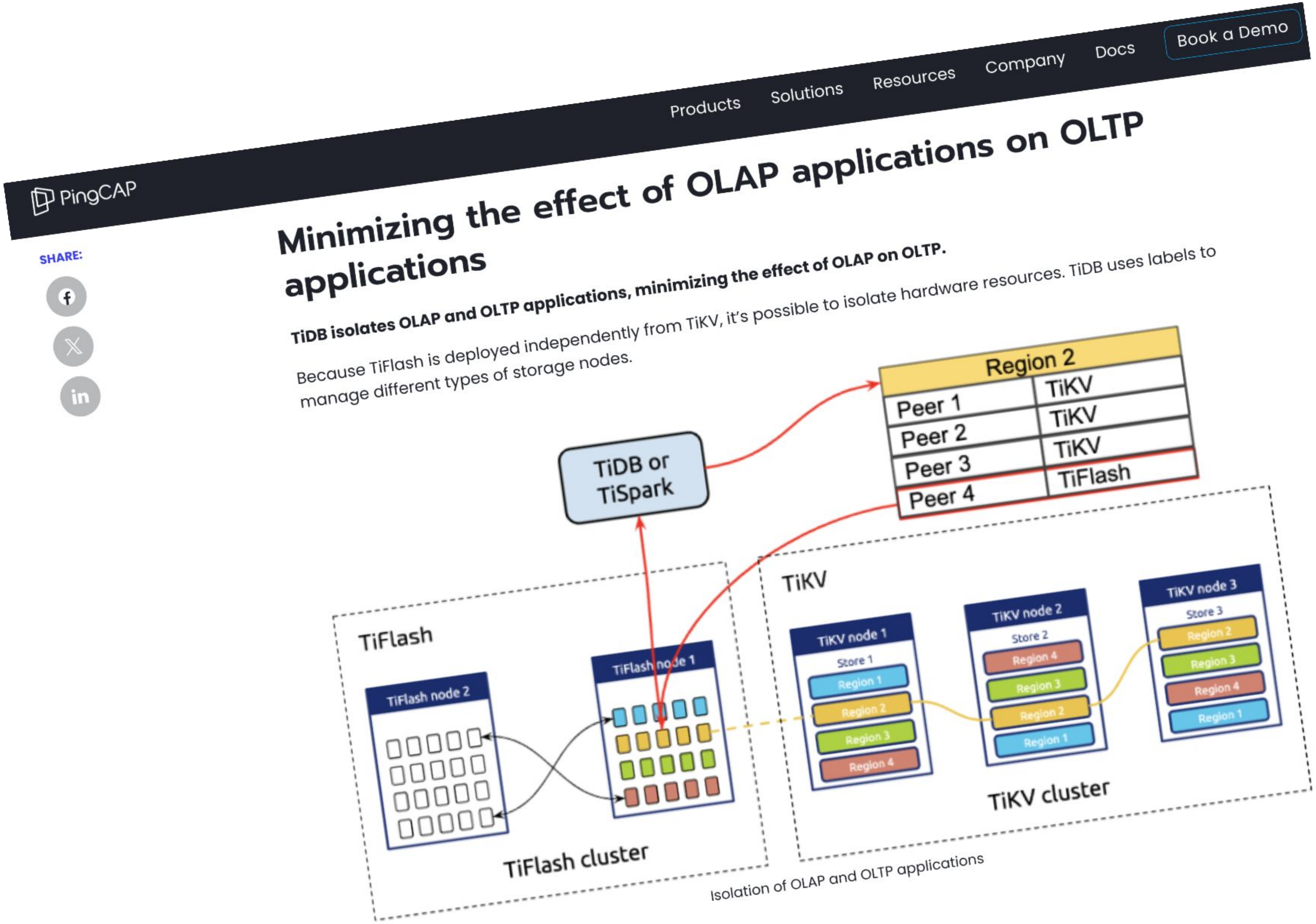
WHY SNOWFLAKE THE DATA CLOUD SOLUTIONS RESOURCES COMPANY CONTACT START FOR FREE

WORKLOADS

SNOWFLAKE UNISTORE

Simplify development by uniting transactional and analytical data.





PingCAP

Products Solutions Resources Company Docs Book a Demo

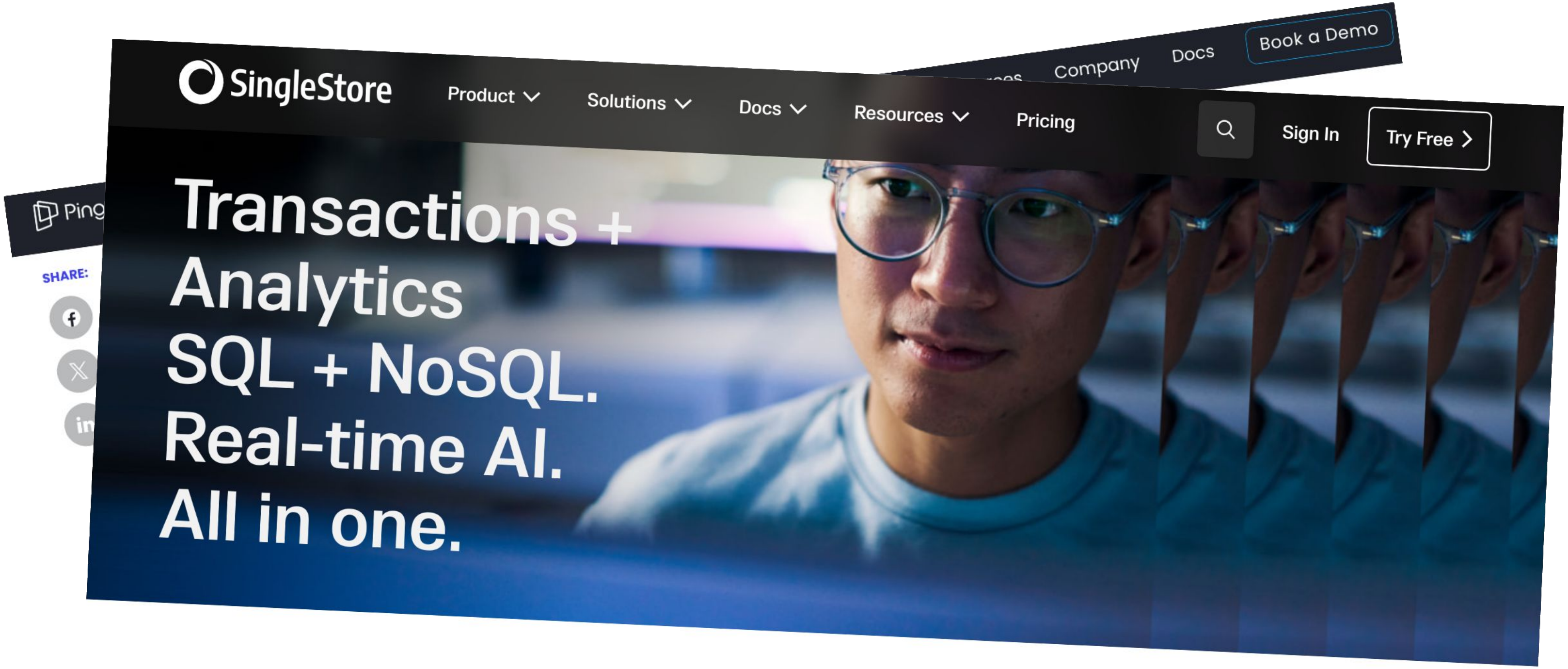
SHARE:

Minimizing the effect of OLAP applications on OLTP applications

TiDB isolates OLAP and OLTP applications, minimizing the effect of OLAP on OLTP.

Because TiFlash is deployed independently from TiKV, it's possible to isolate hardware resources. TiDB uses labels to manage different types of storage nodes.

Isolation of OLAP and OLTP applications



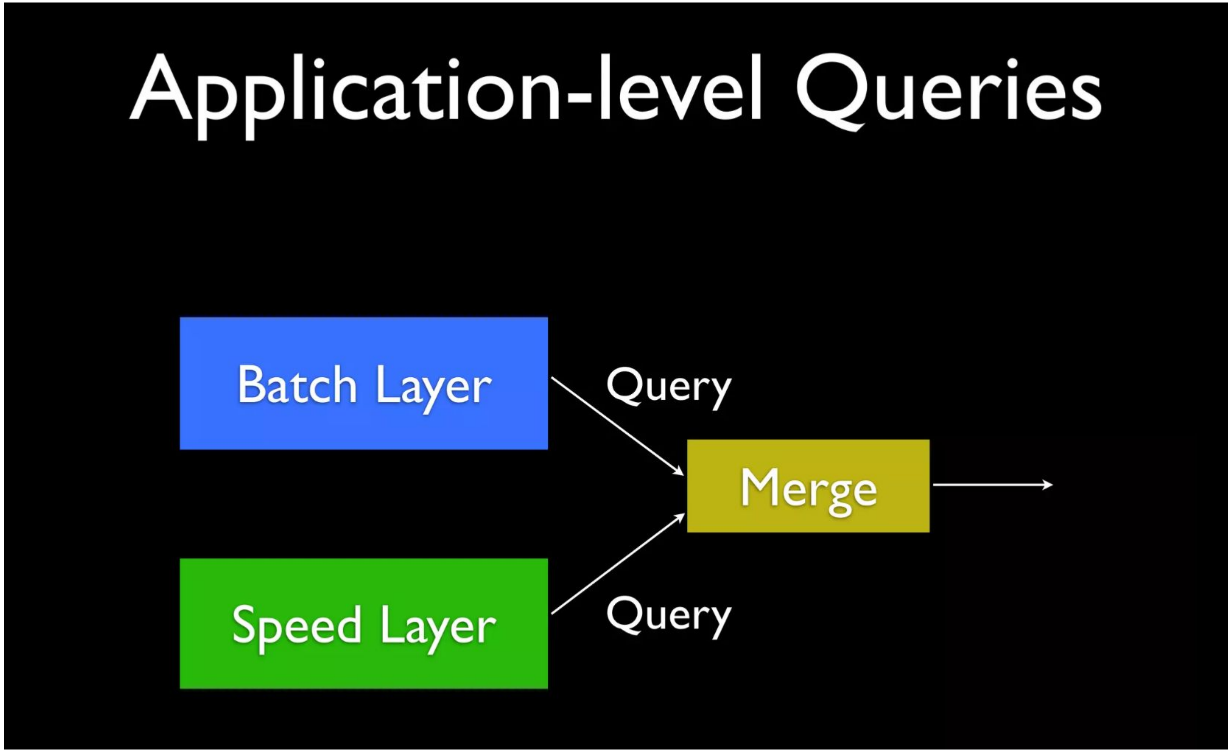
Transact, analyze and contextualize your data in real time.

SingleStoreDB empowers the world's makers to build, deploy and scale modern, intelligent applications — leading to real-time decisions, lasting customer experiences.

SingleStoreDB is a distributed SQL database that offers high-throughput transactions (inserts and upserts), low-latency analytics and context from real-time vector data.

SingleStoreDB meets you wherever you are in your cloud journey — giving you flexibility to deploy wherever you need: self-managed on-premises, or as a fully managed cloud service.

The Lamda Architecture for “real time” analytics



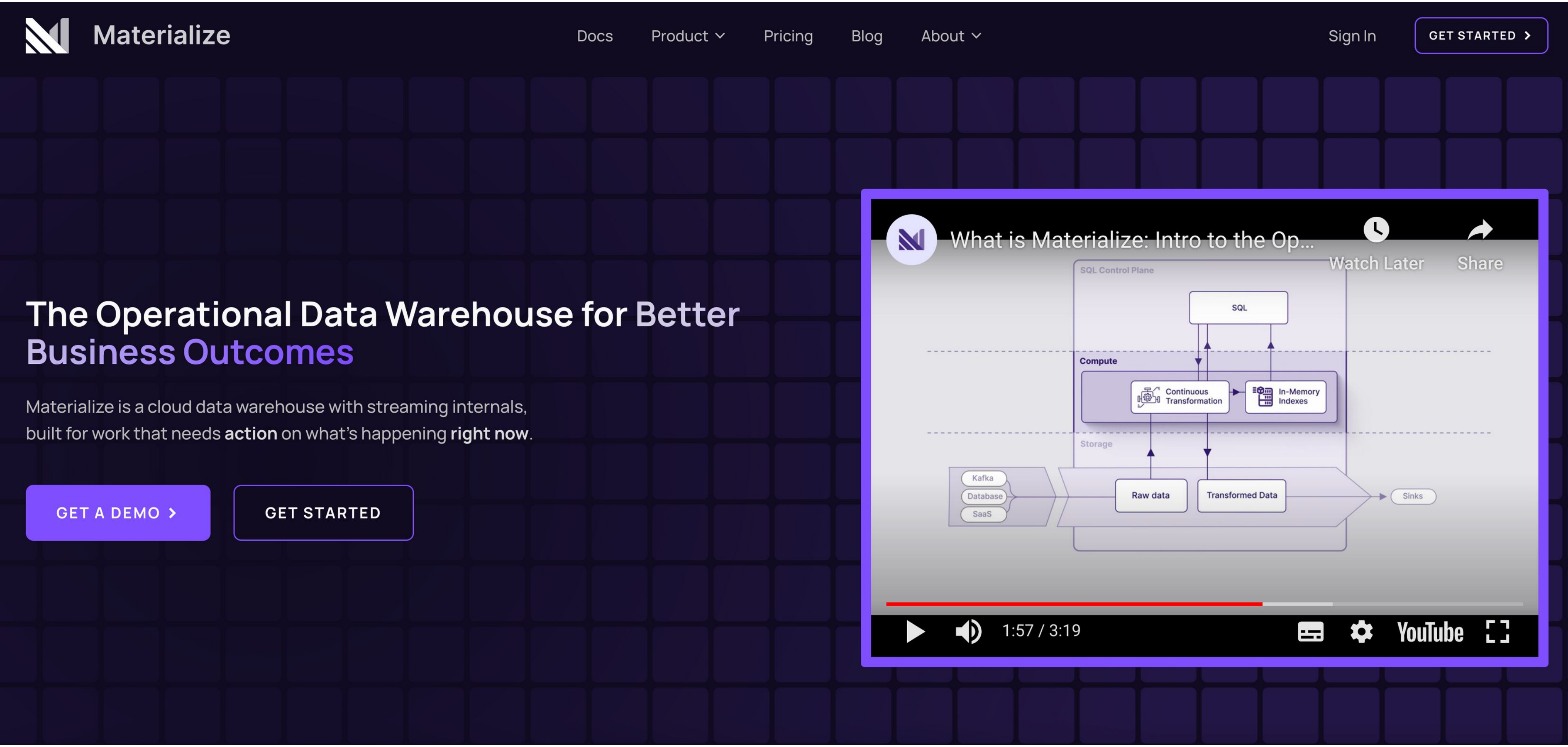
Columnar data
is good for
***batch***

See also:

beam

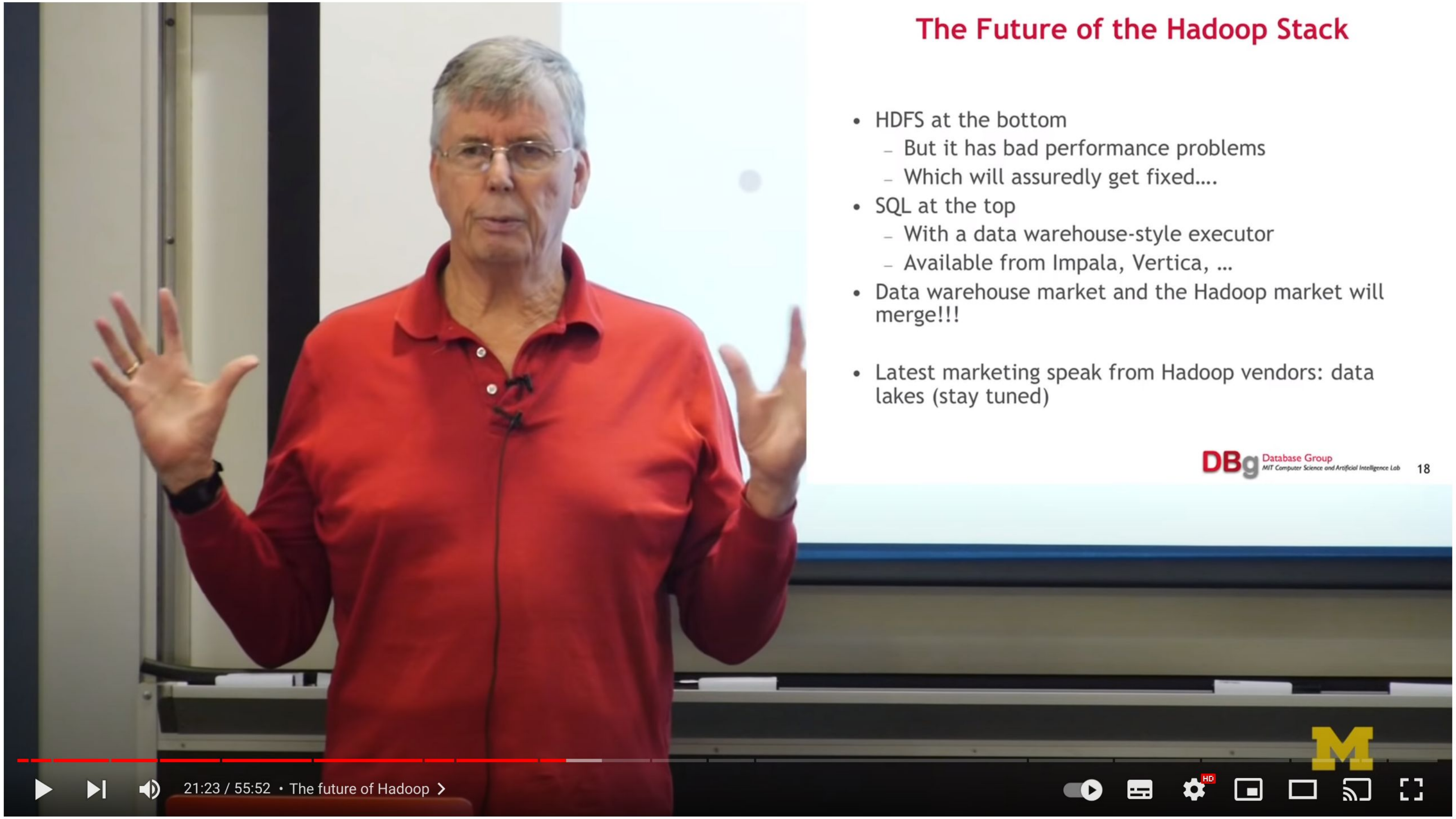
Flink

Google
DataFlow


Materialize
Docs
Product
Pricing
Blog
About
Sign In
GET STARTED
The Operational Data Warehouse for Better Business Outcomes
Materialize is a cloud data warehouse with streaming internals, built for work that needs action on what's happening right now.
GET A DEMO
GET STARTED
What is Materialize: Intro to the Op...
Watch Later
Share
SQL Control Plane
SQL
Compute
Continuous Transformation
In-Memory Indexes
Storage
Kafka
Database
SaaS
Raw data
Transformed Data
Sinks
1:57 / 3:19
YouTube

R&D

https://www.youtube.com/watch?v=KRcecxdGxvQ



Michael Stonebraker | Big Data is (at least) Four Different Problems

Michigan Engineering
44.6K subscribers
Subscribe

380 Share Download Clip Save ...

25K views 6 years ago
Big Data is (at least) Four Different Problems
Michael Stonebraker, Co-Director, Intel Science & Technology Center, MIT

Foundations and Trends® in Databases
Vol. 5, No. 3 (2012) 197–280

DOI: 10.1561/1900000024

now
the essence of knowledge

The Design and Implementation of Modern Column-Oriented Database Systems

Daniel Abadi
Yale University
dna@cs.yale.edu

Peter Boncz
CWI
P.Boncz@cwi.nl

Stavros Harizopoulos
Amiato, Inc.
stavros@amiato.com

Stratos Idreos
Harvard University
stratos@seas.harvard.edu

Samuel Madden
MIT CSAIL
madden@csail.mit.edu

https://stratos.seas.harvard.edu/files/stratos/files/columnstoresfntdbs.pdf

Cornell University

arXiv > cs > cs.DB

Databases

Authors and titles for cs.DB in Aug 2023

[total of 86 entries: **1-25** | 26-50 | 51-75 | 76-86]
[showing 25 entries per page: fewer | more | all]

[25] **arXiv:2308.08702** [**pdf**, **other**]

Finding a Second Wind: Speeding Up Graph Traversal Queries in RDBMSs Using Column-Oriented Processing
Mikhail Firsov, Michael Polyntsov, Kirill Smirnov, George Chernishev
Subjects: **Databases (cs.DB)**; Performance (cs.PF)

[9] **arXiv:2309.06051** [**pdf**, **other**]

OmniSketch: Efficient Multi-Dimensional High-Velocity Stream Analytics with Arbitrary Predicates
Wieger R. Punter, Odysseas Papapetrou, Minos Garofalakis
Subjects: **Databases (cs.DB)**

[19] **arXiv:2309.11322** [**pdf**, **other**]

Vector database management systems: Fundamental concepts, use-cases, and current challenges
Toni Taipalus
Comments: 12 pages, 5 figures
Subjects: **Databases (cs.DB)**

https://arxiv.org/list/cs.DB/2308

https://www.scattered-thoughts.net/log/0040/

0040: olap survey, lobster, feldera, innovation, wizard papers, umbra papers, olap papers

Published 2023-09-29

I published a shallow survey of OLAP and HTAP query engines.

The last 2/3rds or so of this post contains all the supporting notes. Also a lot of papers on strategies for low-latency compilation.

https://www.scattered-thoughts.net/log/0041/

Column Sketches: A Scan Accelerator for Rapid and Robust Predicate Evaluation (2018)

Goal is to accelarate column scans regardless of data distribution and workload.

Build a histogram of data. Divide into evenly full buckets. Give each bucket a short binary code.

Evaluate predicates against buckets first, and then scan for matching buckets.

Their experiments demonstrate good performance across different query selectivities with 1 byte codes over uniformly distributed 32 bit integers.

Performance remains identical under data skew, while bitweaving degrades.

Builds much faster than bitweaving too. (Note that BtrBlocks builds histograms anyway - might be able to produce the sketch almost for free.)

https://arxiv.org/pdf/2004.14471.pdf

Mainlining Databases: Supporting Fast Transactional Workloads on Universal Columnar Data File Formats

Tianyu Li
litianyu@mit.edu
MIT

Matthew Butrovich
mbutrovi@cs.cmu.edu
Carnegie Mellon University

Amadou Ngom
angom@cs.cmu.edu
Carnegie Mellon University

Wan Shen Lim
wanshenl@cs.cmu.edu
Carnegie Mellon University

Wes McKinney
wes@ursalabs.org
Ursa Labs

Andrew Pavlo
pavlo@cs.cmu.edu
Carnegie Mellon University

arXiv:2004.14471v1 [cs.DB] 29 Apr 2020

ABSTRACT

The proliferation of modern data processing tools has given rise to open-source columnar data formats. The advantage of these formats is that they help organizations avoid repeatedly converting data to a new format for each application. These formats, however, are read-only, and organizations must use a heavy-weight transformation process to load data from on-line transactional processing (OLTP) systems. We aim to reduce or even eliminate this process by developing a storage architecture for in-memory database management systems (DBMSs) that is aware of the eventual usage of its data and emits columnar storage blocks in a universal open-source format. We introduce relaxations to common analytical data formats to efficiently update records and rely on a lightweight transformation process to convert blocks to a read-optimized layout when they are cold. We also describe how to access data from third-party analytical tools with minimal serialization overhead. To evaluate our work, we implemented our storage engine based on the Apache Arrow format and integrated it into the DB-X DBMS. Our experiments show that our approach achieves comparable performance with dedicated OLTP DBMSs while enabling orders-of-magnitude faster data exports to external data science and machine learning tools than existing methods.

1 INTRODUCTION

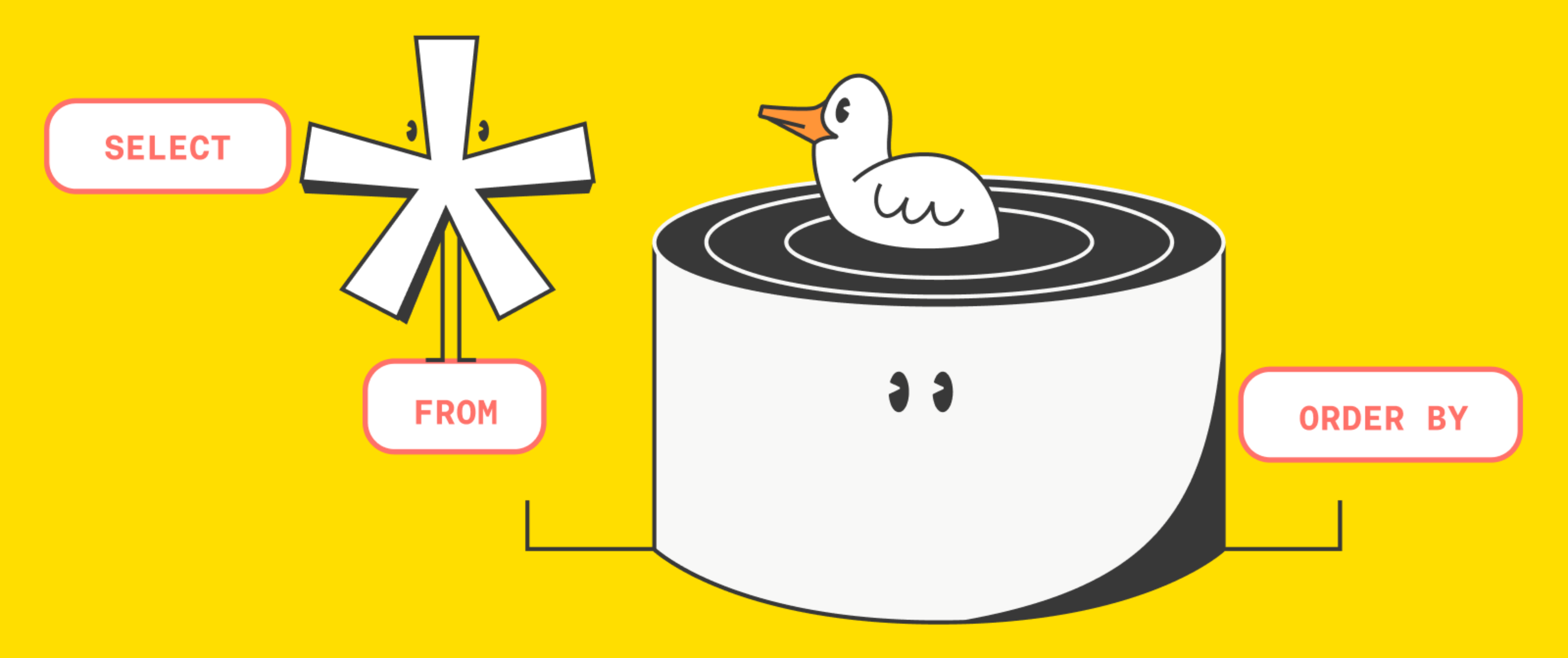
Data analysis pipelines allow organizations to extrapolate insights from data residing in their OLTP systems. The tools in

Although a DBMS can perform some analytical duties, modern data science workloads often involve specialized frameworks, such as TensorFlow, PyTorch, and Pandas. Organizations are also heavily invested in personnel, tooling, and infrastructure for the current data science eco-system of Python tools. We contend that the need for DBMS to efficiently export large amounts of data to external tools will persist. To enable analysis of data as soon as it arrives in a database is, and to deliver performance gains across the entire data analysis pipeline, we should look to improve a DBMS's interoperability with external tools.

If an OLTP DBMS directly stores data in a format used by downstream applications, the export cost is just the cost of network transmission. The challenge in this is that most open-source formats are optimized for read/append operations, not in-place updates. Meanwhile, divergence from the target format in the OLTP DBMS translates into more transformation overhead when exporting data, which can be equally detrimental to performance. A viable design must seek equilibrium in these two conflicting considerations.

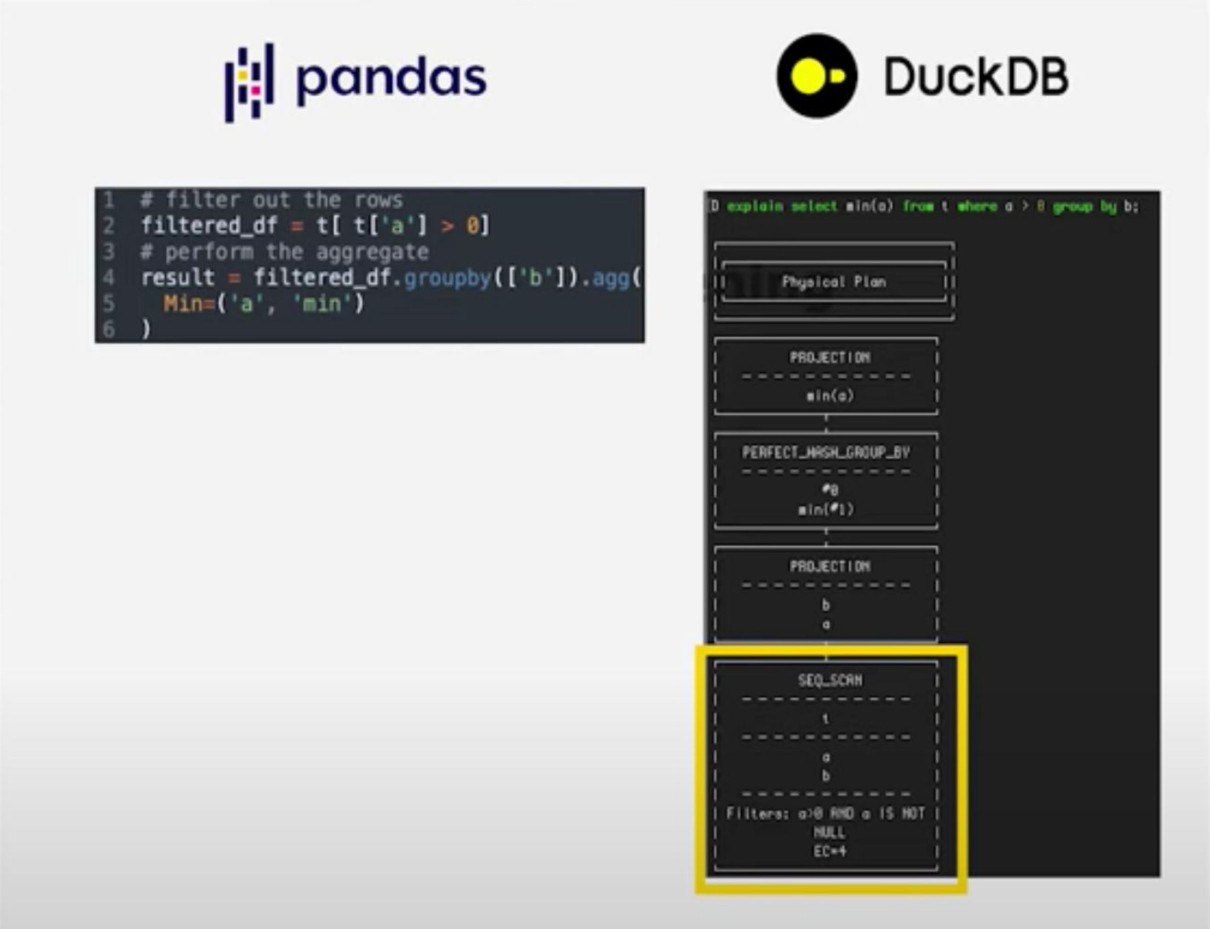
To address this challenge, we present a multi-versioned DBMS that operates on a relaxation of an open-source columnar format to support efficient OLTP modifications. The relaxed format can then be transformed into the canonical format as data cools with a light-weight in-memory process. We implemented our storage and concurrency control architecture in **DB-X** [10] and evaluated its performance. We target Apache Arrow, although our approach is also appli-

DuckDB...



End-to-end-query optimization

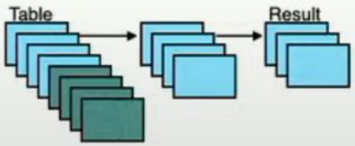
- Expression rewriting
- Join ordering
- Subquery flattening
- Filter / projection pushdown
  - Automatic in DuckDB
  - Manual in Pandas

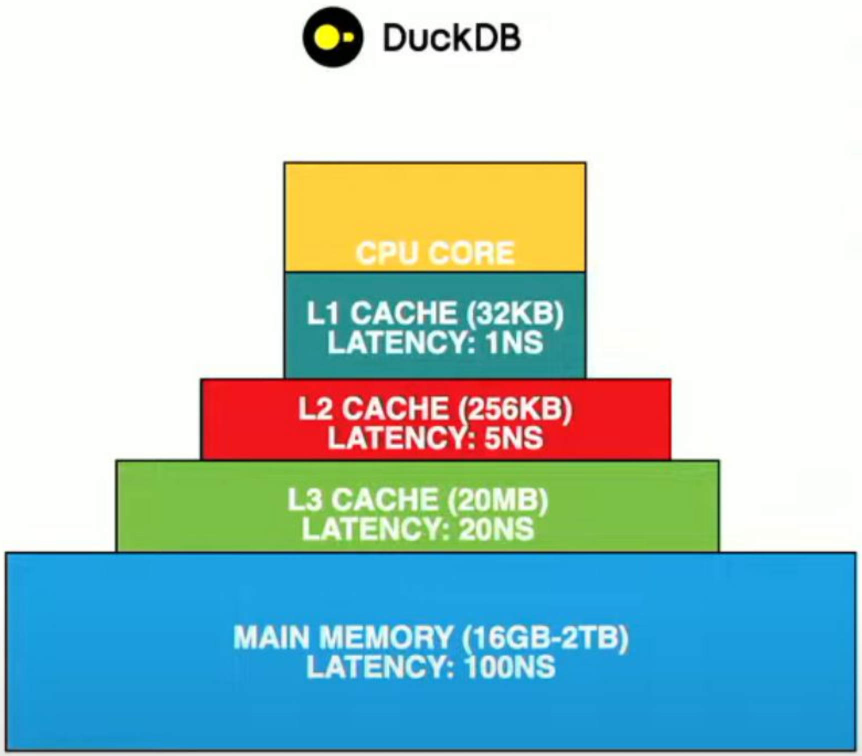


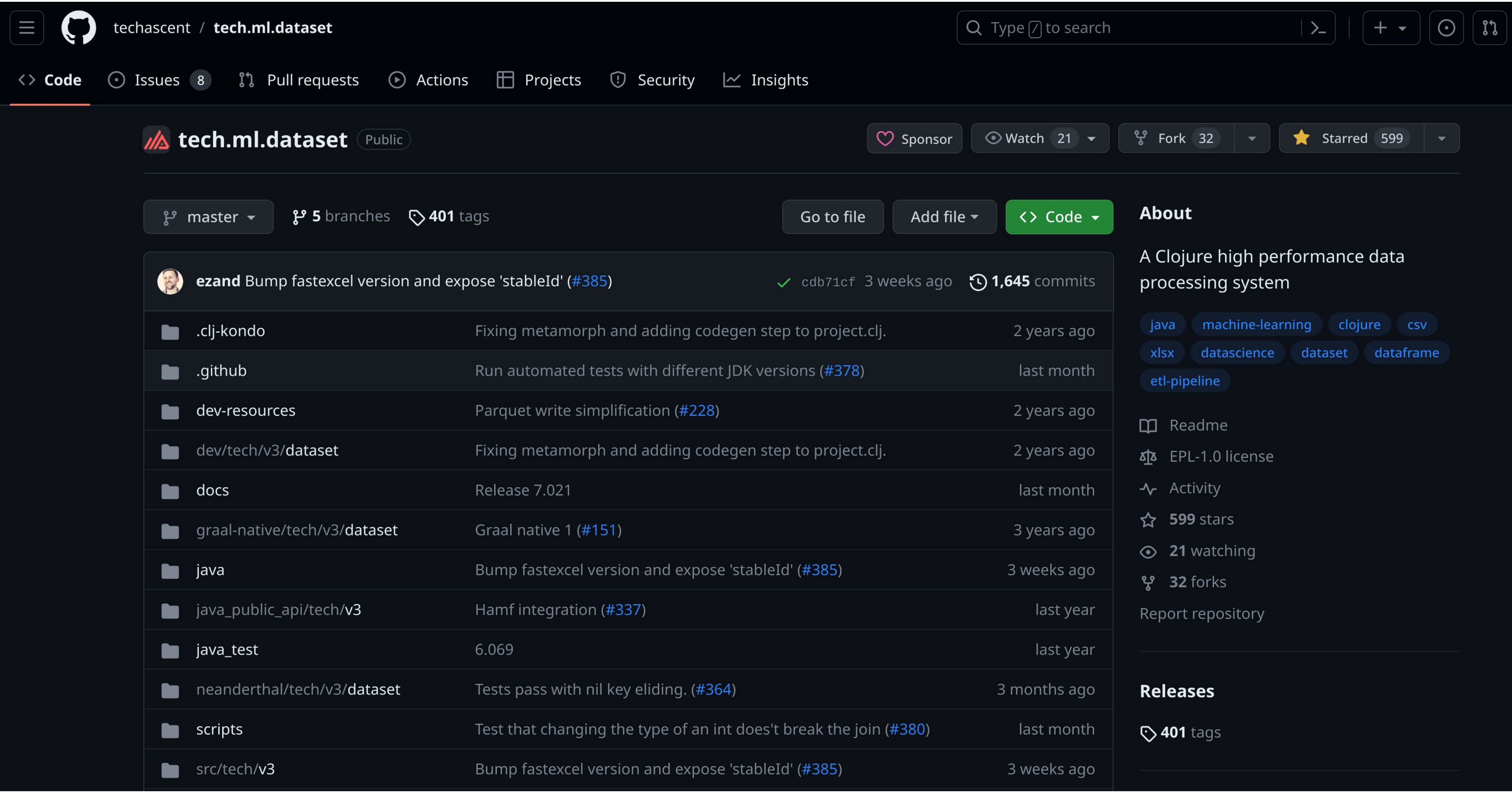
Execution

- Vectorized Processing (DuckDB)
  - Optimized for CPU Cache locality
  - SIMD instructions, Pipelining
  - Small intermediates (ideally fit in L1 cache)

Vectorized Processing







https://github.com/techascent/tech.ml.dataset

Accessing this from Clojure, through TMD, is also easy:

```
user> (require '[tmducken.duckdb :as duckdb])
nil
user> (require '[tech.v3.dataset :as ds])
nil
user> (duckdb/initialize!)
Sep 06, 2023 11:00:12 AM clojure.tools.logging$eval7454$fn__7457 invoke
INFO: Attempting to load duckdb from "./binaries/libduckdb.so"
true
user> (def db (duckdb/open-db "data.ddb"))
#'user/db
user> (def conn (duckdb/connect db))
#'user/conn
user> (time (duckdb/sql->dataset conn "SELECT COUNT(*) AS n FROM data"))
"Elapsed time: 10.305756 msecs"
:_unnamed [1 1]:

|         n |
|----------:|
| 400000000 |
```

Object Store Table Formats – columns without a database

1) Open standards for huge, petabyte-scale analytic tables that are accessible for heterogeneous processing/querying - using Spark DataFrames, SparkSQL, Dremio, Trino/Presto, etc.
2) “ACID for Big Data”
3) “Think about data, not about files” - “a table format is a way to organize a dataset’s files to present them as a single table”
4) Efficient columnar storage within immutable file objects, e.g. Apache Parquet
5) Lightweight indexes and metadata
6) Transactional (i.e. put and delete, with full isolation)

Leading Open Table Formats

1) Databricks' Delta Lake
2) Apache Hudi - donated by Uber, built to avoid batch processing with Spark+HDFS - focussed on eventing
3) Apache Iceberg - donated by Netflix, built to replace Hive due to correctness issues, also used by Apple, Twitter, Expedia, etc.

A Thorough Comparison of Delta Lake, Iceberg and Hudi

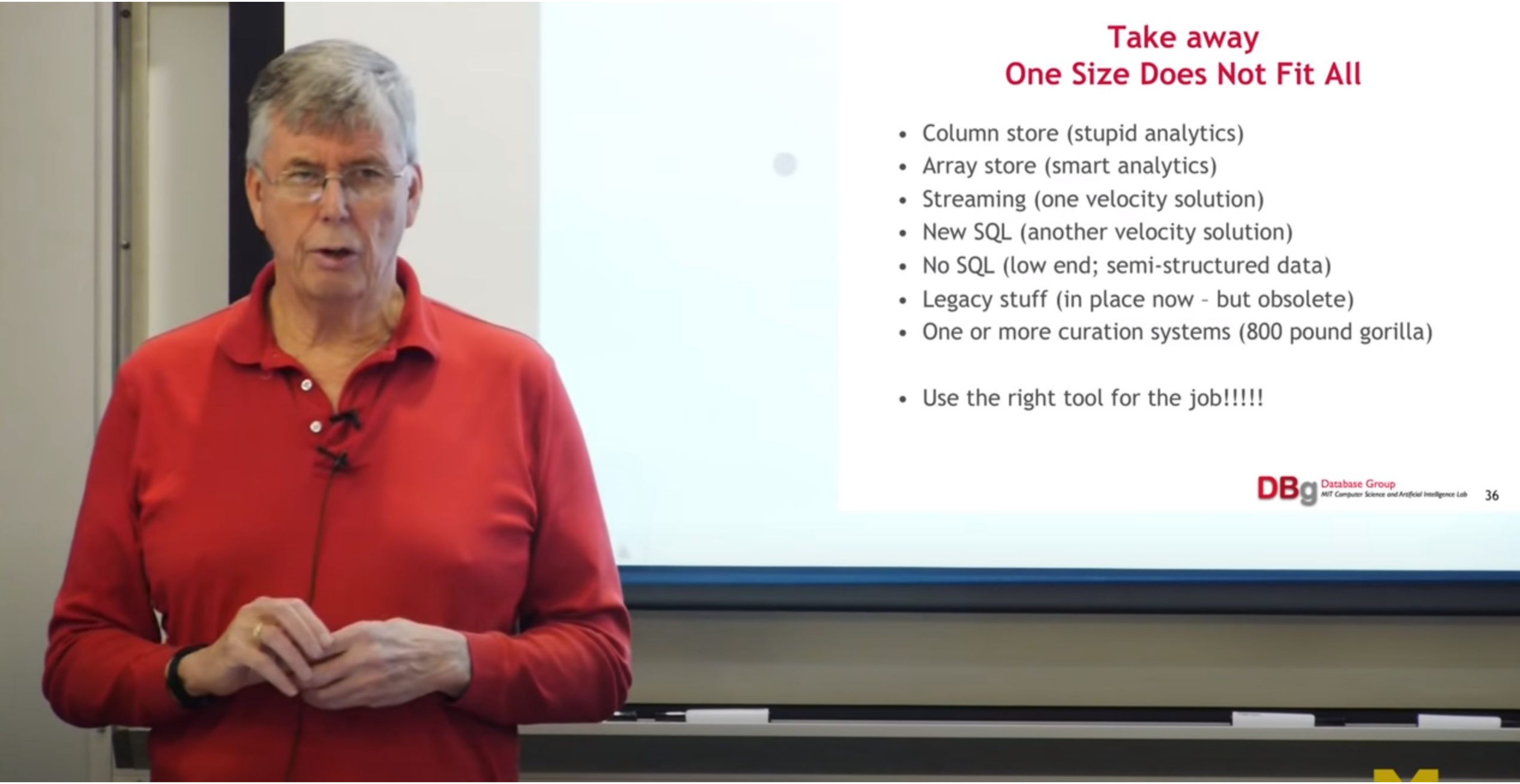
A Quick Comparison

2020-05

	Delta Lake (open source)	Apache Iceberg	Apache Hudi
Transaction (ACID)	Y	Y	Y
MVCC	Y	Y	Y
Time travel	Y	Y	Y
Schema Evolution	Y	Y	Y
Data Mutation	Y (update/delete/merge into)	N	Y (upsert)
Streaming	Sink and source for spark struct streaming	Sink and source(wip) for Spark struct streaming, Flink (wip)	DeltaStreamer HiveIncrementalPuller
File Format	Parquet	Parquet, ORC, AVRO	Parquet
Compaction/Cleanup	Manual	API available (Spark Action)	Manual and Auto
Integration	DSv1, Delta connector	DSv2, InputFormat	DSv1, InputFormat
Multiple language support	Scala/java/python	Java/python	Java/python
Storage Abstraction	Y	Y	N
API dependency	Spark-bundled	Native/Engine bundled	Spark-bundled
Data ingestion	Spark, presto, hive	Spark, hive	DeltaStreamer

2023 Update:
Still no clear winner
(but probably Iceberg)

https://www.youtube.com/watch?v=Wx8G08jaedo

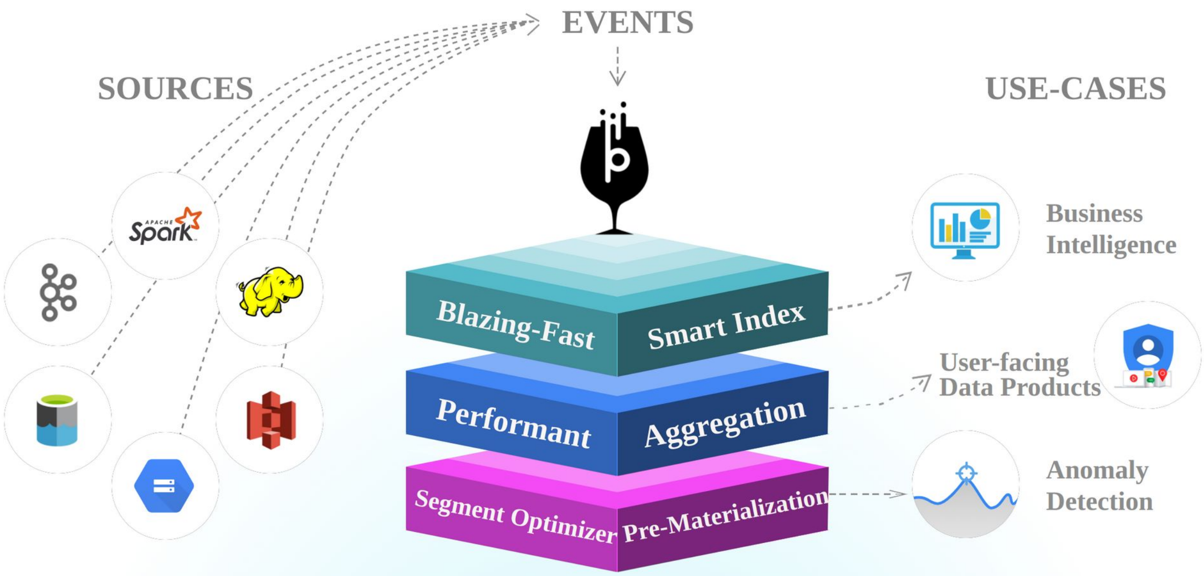


https://www.youtube.com/watch?v=KRcecxdGxvQ

RELEASE v0.11.0 has been released! Check the release notes

Apache Pinot™

Realtime distributed OLAP datastore, designed to answer OLAP queries with low latency



Getting Started

Join our Slack

Pinot is proven at **scale in LinkedIn** powers 50+ user-facing apps and serving **100k+ queries**

About ClickHouse

Blazing fast
Exceeds other column-oriented database management systems

Linearly scalable
Incredible scaling both horizontally and vertically

Fault tolerant
Supports async replication and can be deployed across multiple datacenters

Hardware efficient
Processes analytical queries faster than traditional row-oriented systems

Highly reliable
Purely distributed system, including enterprise-grade security

Feature-rich
User-friendly SQL query dialect, built-in analytics capabilities, and more

Why choose ClickHouse?

Blazing fast

ClickHouse uses all available hardware to its full potential to process each query as fast as possible. Peak processing performance for a single query stands at more than 2 terabytes per second (after decompression, only used columns). In distributed setup reads are automatically balanced among healthy replicas to avoid increasing latency.

Fault-tolerant

ClickHouse supports multi-master asynchronous replication and can be deployed across multiple datacenters. All nodes are equal, which allows avoiding having single points of failure. Downtime of a single node or the whole datacenter won't affect the system's availability for both reads and writes.

Easy to use

ClickHouse is simple and works out-of-the-box. It streamlines all your data processing: ingest all your structured data into the system and it becomes instantly available for building reports. SQL dialect allows expressing the desired result without involving any custom non-standard API that could be found in some DBMS.

Highly reliable

ClickHouse can be configured as a purely distributed system located on independent nodes, without any single points of failure. It also includes a lot of enterprise-grade security features and fail-safe mechanisms against human errors.

Welcome to TileDB Cloud!

TUTORIALS

Start Here!

Product Tour

Serverless Compute 101

Task Graphs 101

Use Cases

CONCEPTS

Universal Data Management

Serverless Compute

Console and API

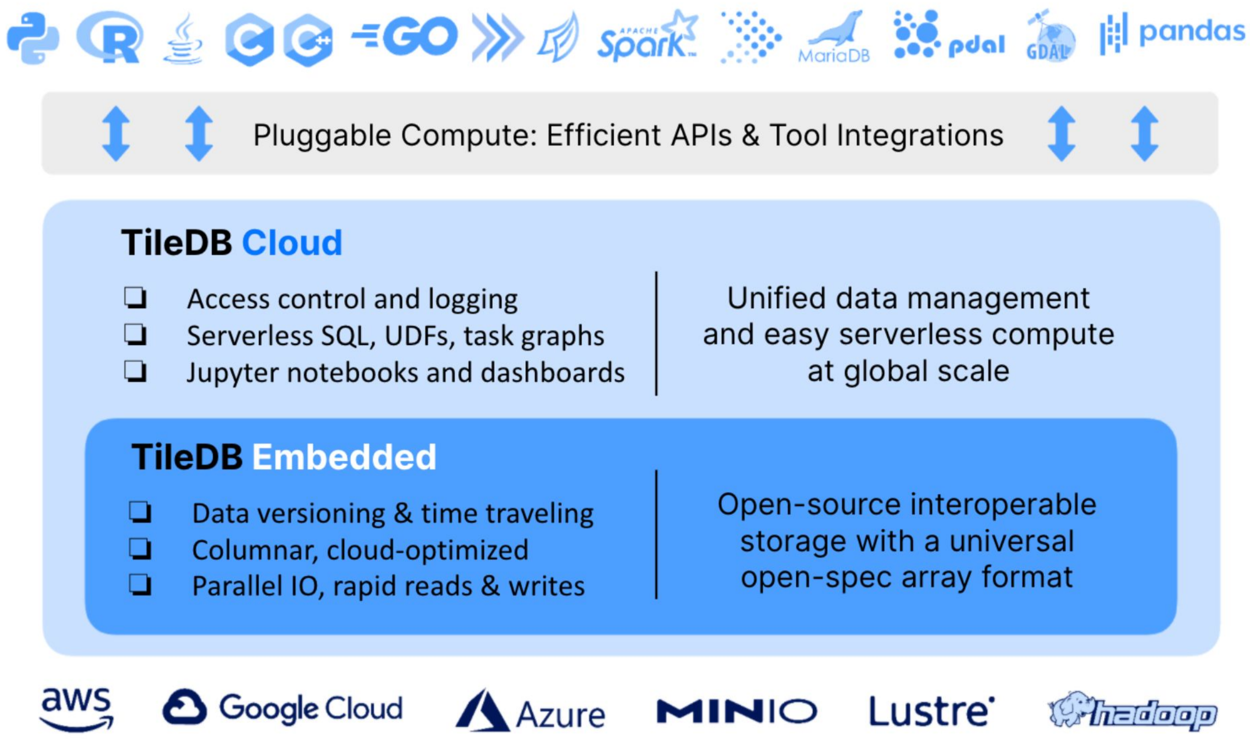
TileDB Cloud Internals

Pricing and Billing

Marketplace

HOW TO

TileDB Cloud is based on the TileDB Embedded open-source universal storage engine, which models and efficiently stores all data as (dense or sparse) **multi-dimensional arrays**, providing a common API and a large number of APIs and tool integrations.



The TileDB Cloud stack at a glance

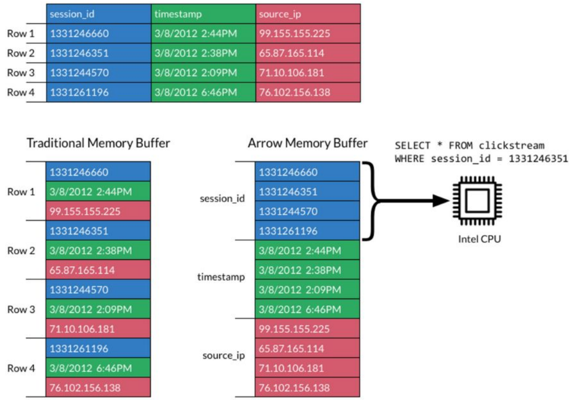
Apache Arrow Overview

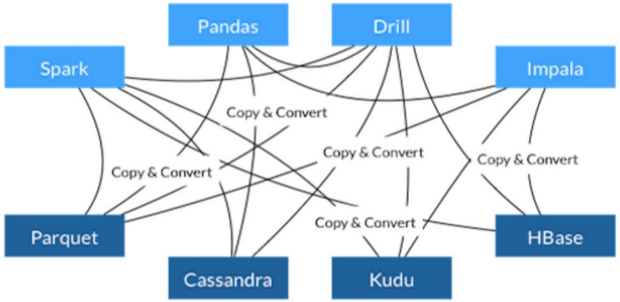
Apache Arrow is a software development platform for building high performance applications that process and transport large data sets. It is designed to both improve the performance of analytical algorithms and the efficiency of moving data from one system or programming language to another.

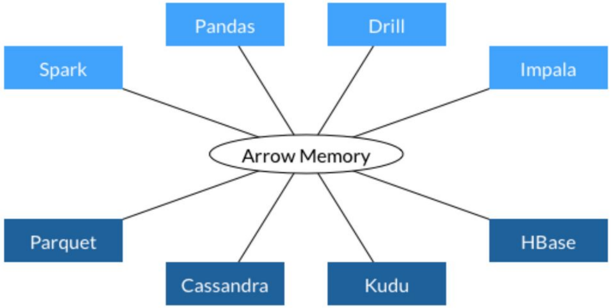
A critical component of Apache Arrow is its **in-memory columnar format**, a standardized, language-agnostic specification for representing structured, table-like datasets in-memory. This data format has a rich data type system (included nested and user-defined data types) designed to support the needs of analytic database systems, data frame libraries, and more.

Columnar is Fast

The Apache Arrow format allows computational routines and execution engines to maximize their efficiency when scanning and iterating large chunks of data. In particular, the contiguous columnar layout enables vectorization using the latest SIMD (Single Instruction, Multiple Data) operations included in modern processors.







Standardization Saves

Without a standard columnar data format, every database and language has to implement its own internal data format. This generates a lot of waste. Moving data from one system to another involves costly serialization and deserialization. In addition, common algorithms must often be rewritten for each data format.

Arrow's in-memory columnar data format is an out-of-the-box solution to these problems. Systems that use or support Arrow can transfer data between them at little-to-no cost. Moreover, they don't need to implement custom connectors for every other system. On top of these savings, a standardized memory format facilitates reuse of libraries of algorithms, even across languages.

Arrow Libraries

The Arrow project contains libraries that enable you to work with data in the Arrow columnar format in many languages. The C++, C#, Go, Java, JavaScript, Julia, and Rust libraries contain distinct implementations of the Arrow format. These libraries are integration-tested against each other to ensure their fidelity to the format. In addition, Arrow libraries for C (Glib), MATLAB, Python, R, and Ruby are built on top of the C++ library.

1.2 Standardizing on Arrow

Arrow is an open source project that enables developers to efficiently build fast, interoperable data systems based on open standards. The Arrow project ticks all the boxes for a solid standard:

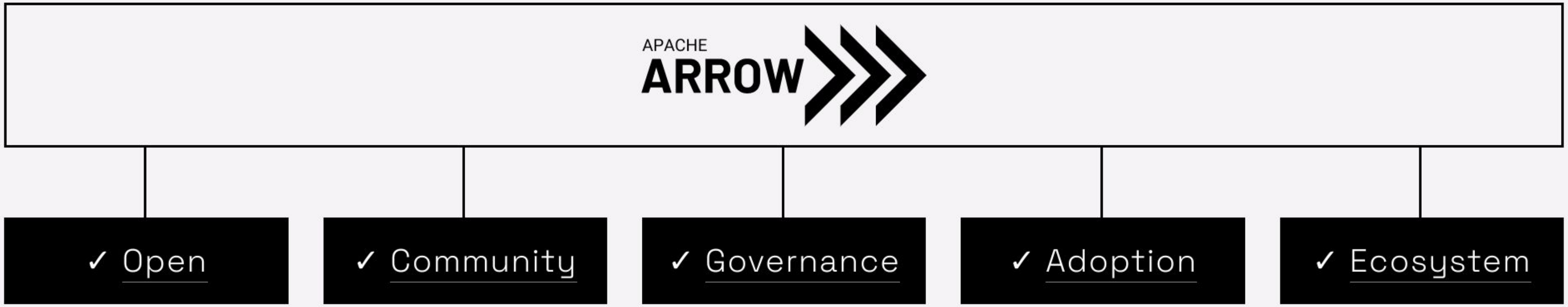


Figure 01.06. Arrow is a standard that we build with and trust, in part based on these five factors.

1.2.1 The Arrow format

Arrow started as a standardized in-memory format for structured tabular data. Why start there? Because when you are building data-intensive analyses and applications, systems get stuck on two main tasks:

1. **Moving data**

   When a workload is **transport-bound** (or input/output[I/O]-bound), the speed of execution depends on the rate of transfer of data into or out of a system.

2. **Processing data**

   When a workload is **compute-bound**, the speed of execution depends on the speed of the processor, whether it is a CPU, GPU, or another type of hardware.

Apache Arrow

APACHE ARROW

- Columnar Format
- Interprocess and in-process (C) protocols
- Query Engine Components
- IO / File Format Backends
- Flight & FlightSQL
- JIT Expression Compilation

Apache Arrow is **doing for data analytics what LLVM did for compiler infrastructure**. Modular, reusable software components for building high-performance analytics systems.

GO

JS

R

Andy Pavlo
@andy_pavlo

Arrow has become a toolkit of components for building an OLAP DBMS: file format, execution engine, file storage, expression eval, networking protocol/transport.
If you've ever worked on a DBMS, you know that these things are hard to build. Arrow provides them for you.

8:01 PM · Dec 15, 2021 · Twitter Web App

1 Retweet 1 Quote Tweet 10 Likes

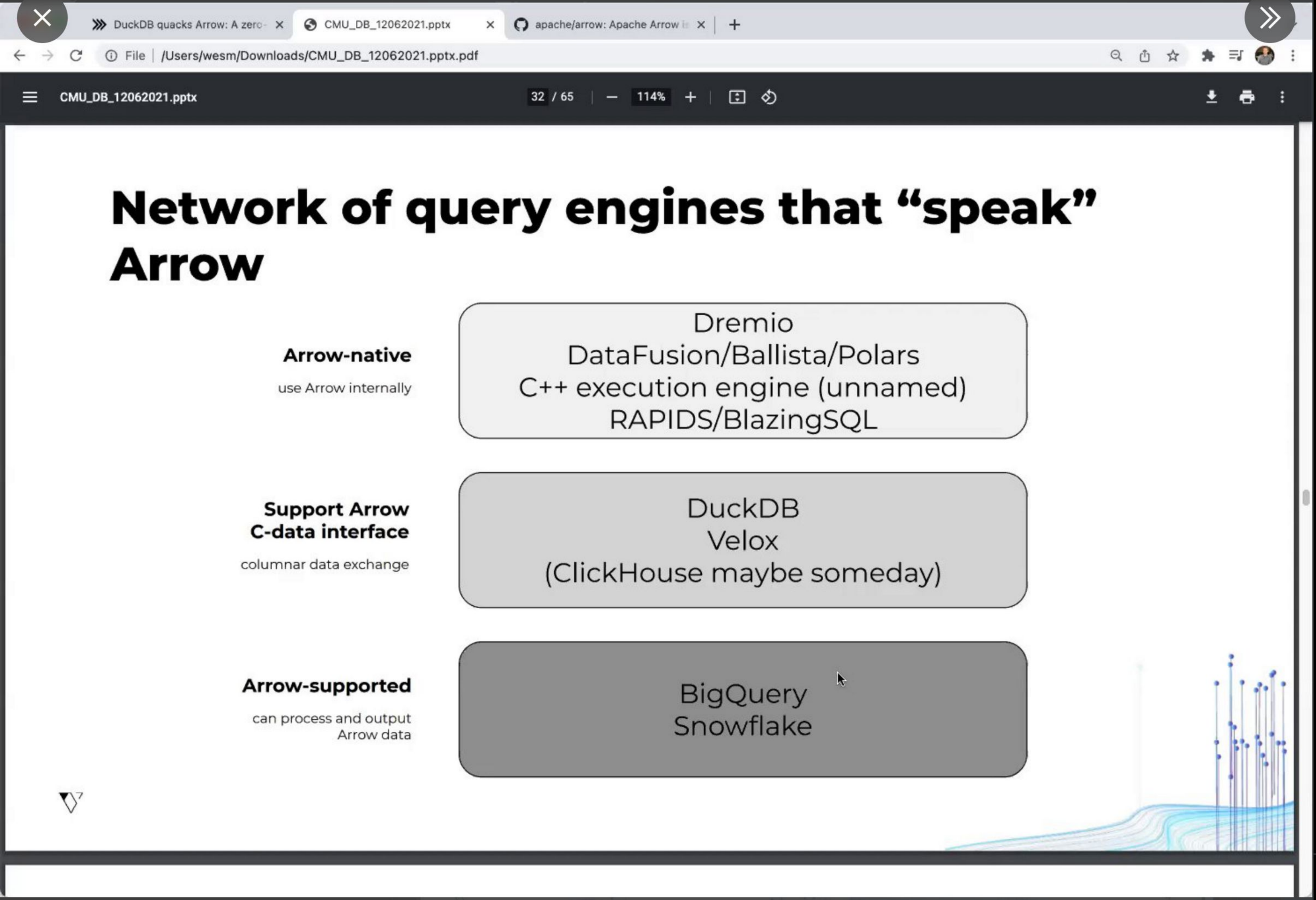
Tweet your reply Reply

Andy ... @a... · Dec 15, 2021
Replying to @andy_pavlo
The idea of composable DBMS parts is not new. Back the late 1990s, @surajitc proposed building RISC-

Jeremy Taylor
@refset

8:01 PM · Dec 15, 2021 · Twitter Web App

1 2 10



Andy Pavlo
@andy_pavlo

To build a complete DBMS using @ApacheArrow you still need a SQL parser, optimizer, buffer pool manager, and storage layer. @duckdb is a good example of how to do this, although they don't use Arrow's Flight SQL and other parts. @InfluxDB is working on a new Arrow-engine too.

8:01 PM · Dec 15, 2021 · Twitter Web App

Search projects

Help Sponsors Log in Register

pyarrow 14.0.1

```
pip install pyarrow
```

Latest version

Released: Nov 8, 2023

Python library for Apache Arrow

Navigation

- Project description
- Release history
- Download files

Project description

Python library for Apache Arrow

pypi v14.0.1 conda-forge

This library provides a Python API for functionality provided by the Arrow C++ libraries, along with tools for Arrow integration and interoperability with pandas, NumPy, and other software in the Python ecosystem.

DuckDB

Documentation Blog GitHub Contributing

DuckDB is an in-process SQL OLAP database management system

Installation ↓ Documentation Live Demo

Why DuckDB?

Simple

- In-process, serverless
- C++11, no dependencies, single file build
- APIs for Python/R/Java/...

more →

Feature-rich

- Transactions, persistence
- Extensive SQL support
- Direct Parquet & CSV querying

more →

Fast

- Vectorized engine
- Optimized for analytics
- Parallel query processing

more →

Free

- Free & Open Source
- Permissive MIT License

more →

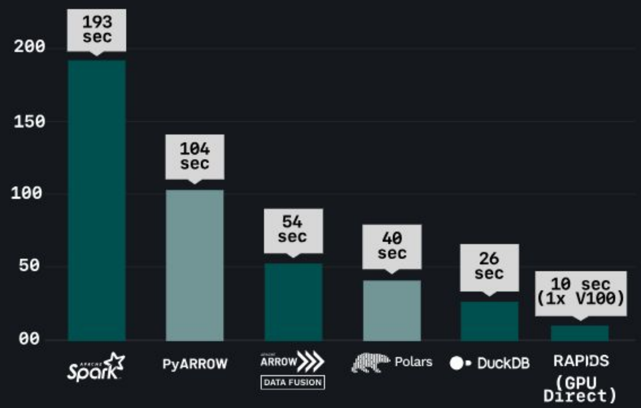
Compare data engines running 17GB of Parquet data on GPUs and CPUs

Hardware

Blog | Single GPU Outperforms 88 CPUs by 2.5X

GPUs are essential for machine learning and AI at enterprise scale – and are becoming increasingly critical for data preprocessing workloads. Recent benchmarking showed how a single NVIDIA V100 GPU outperforms a total of 88 x86 CPU cores by ~2.5X. This also showed a single GPU running on RAPIDS outperforms Spark on an 88 core cluster by 20X. Get the full results in this featured resource.

System Specifications	
GPUs	2x V100 32 GB
GPU Memory	64 GB Total
CPUs	2x E5-2699V4, 88 Cores Total
System Memory	1TB
Storage	4TB, 4x 1TB NVMe



↳ Benchmarking Data Engines

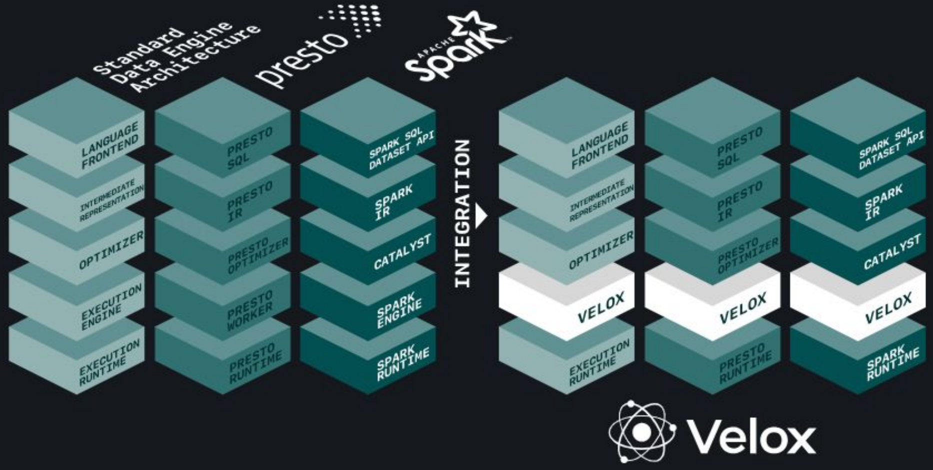
Swap Java-based engines with Velox for a 3X perf improvement

Velox

Report | Velox: 2023 Project to Watch

Velox is an embeddable columnar database engine designed for Arrow-based systems. This modular, unification standard benefits industries using and developing data management systems. Learn how Velox breaks down data silos and accelerates data processing.

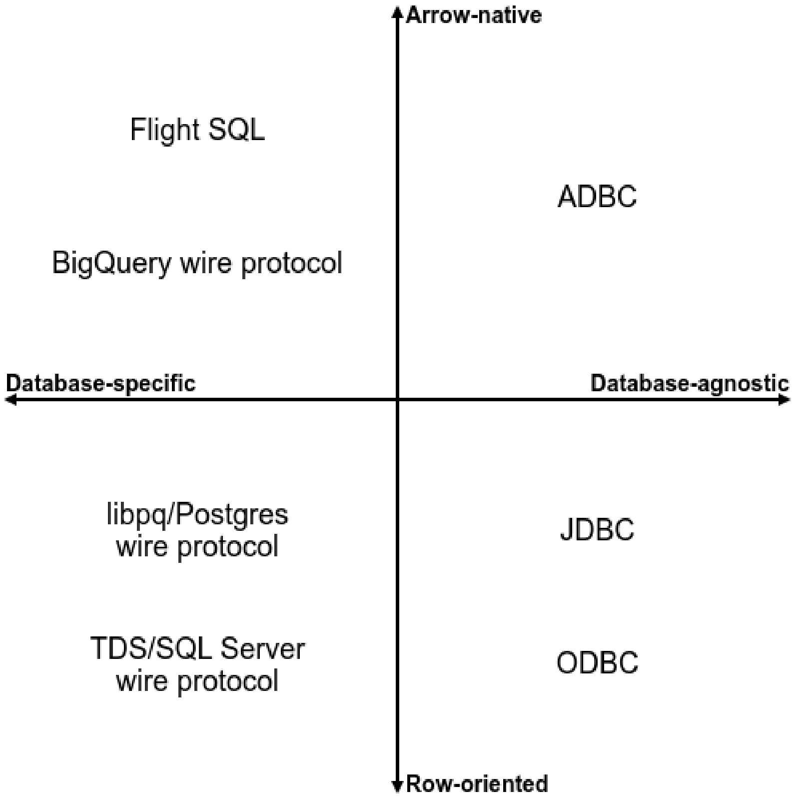
Velox GitHub ↗
Velox Data Thread Talk ↗
Velox Blog ↗
Velox Research Paper from VLDB ↗



↳ Velox Data Infrastructure

"Data management systems like Presto and Spark typically have their own execution engines and other components. Velox can function as a common execution engine across different data management systems."

Source: Facebook Engineering Blog. Diagram by Phillip Bell.


Arrow-native
Flight SQL
ADBC
BigQuery wire protocol
Database-specific
Database-agnostic
libpq/Postgres wire protocol
JDBC
TDS/SQL Server wire protocol
ODBC
Row-oriented

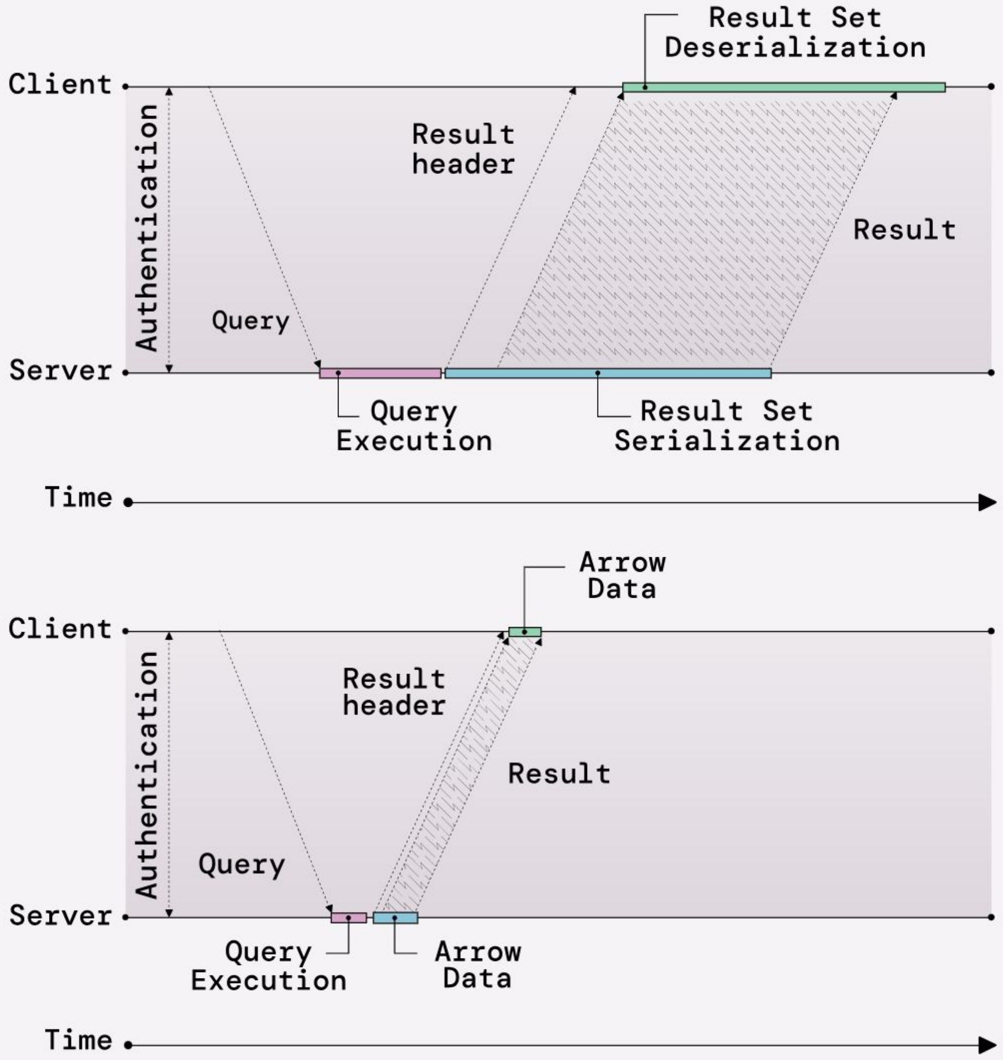
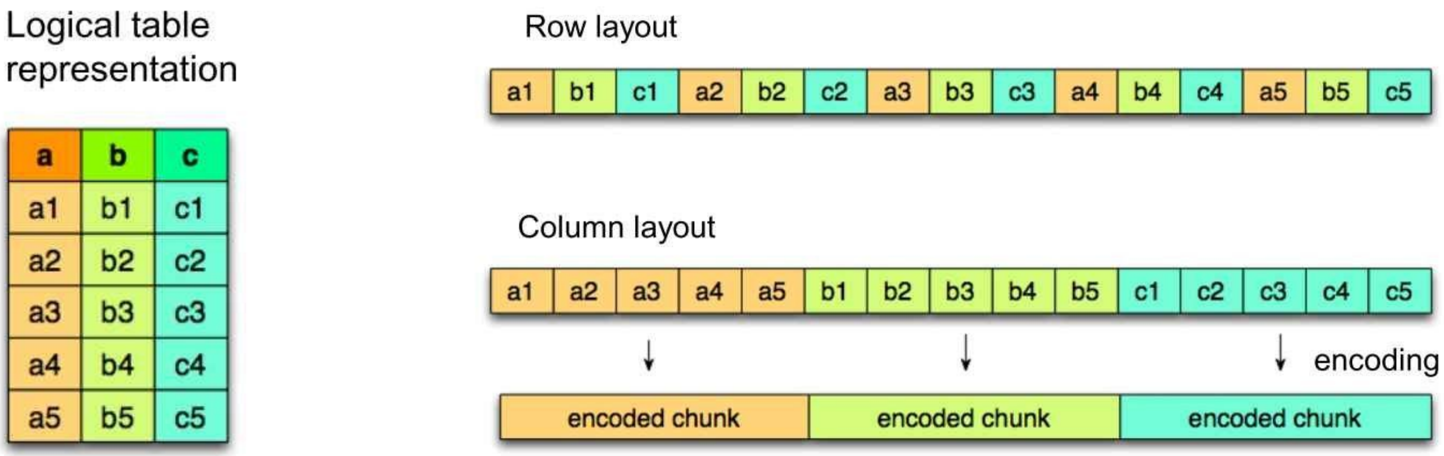


Figure 03.08. Comparison of typical client-server communication versus with Flight. Source: "Benchmarking Apache Arrow Flight - A wire-speed protocol for data transfer, querying and microservices" by Ahmad et al.

Today's Topics

1. ~~Columnar data 101~~
2. ~~Context & trends~~
3. ~~Modern analytic systems~~
4. ~~R&D~~

JUXT


Logical table representation
a b c
a1 b1 c1
a2 b2 c2
a3 b3 c3
a4 b4 c4
a5 b5 c5
Row layout
a1 b1 c1 a2 b2 c2 a3 b3 c3 a4 b4 c4 a5 b5 c5
Column layout
a1 a2 a3 a4 a5 b1 b2 b3 b4 b5 c1 c2 c3 c4 c5
encoding
encoded chunk
encoded chunk
encoded chunk

THANK YOU 🙏

QUESTIONS?

jdt@juxt.pro
@refset

JUXT