ADVANCED
DATABASE
SYSTEMS

Data Formats & Encoding I

02

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OBSERVATION

OLAP workloads perform ***sequential scans*** on large segments of read-only data.

→ The DBMS only needs to find individual tuples to "stitch" them back together.

OLTP workloads use indexes to find individual tuples without performing sequential scans.

→ Tree-based indexes (B+Trees) are meant for queries with low selectivity predicates.

→ Also need to accommodate incremental updates.

SEQUENTIAL SCAN OPTIMIZATIONS

Data Encoding / Compression
Prefetching
Parallelization
Clustering / Sorting
Late Materialization
Materialized Views / Result Caching
Data Skipping
Data Parallelization / Vectorization
Code Specialization / Compilation

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TODAY'S AGENDA

Storage Models

Persistent Data Formats

STORAGE MODELS

A DBMS's ***storage model*** 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)

COLUMN-STORES VS. ROW-STORES: HOW DIFFERENT ARE THEY REALLY?
SIGMOD 2008

N-ARY STORAGE MODEL (NSM)

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

Ideal for OLTP workloads where txns tend to access individual entities and insert-heavy workloads.
→ Use the tuple-at-a-time ***iterator processing model***.

NSM database page sizes are typically some constant multiple of **4 KB** hardware pages.
→ Example: Oracle (4 KB), Postgres (8 KB), MySQL (16 KB)

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.

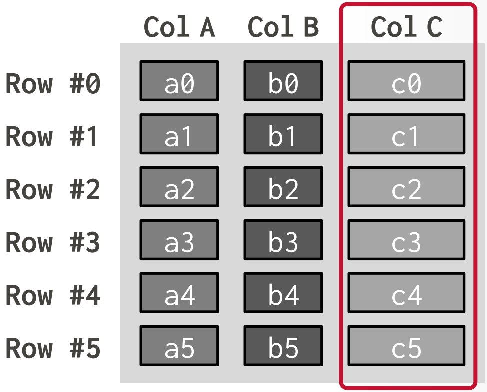
→ Use a batched ***vectorized processing model***.

File sizes are larger (100s of MBs), but it may still organize tuples within the file into smaller groups.

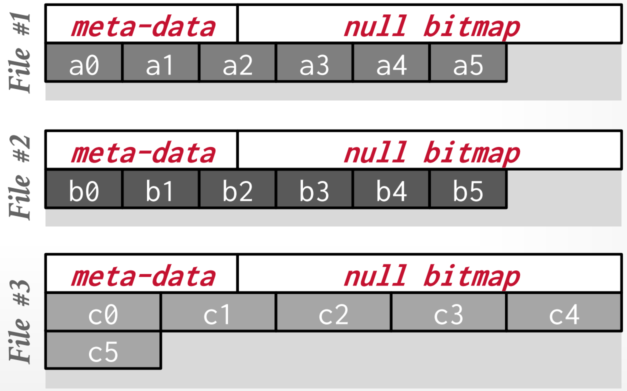
DSM: PHYSICAL ORGANIZATION

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.



Maintain a separate file per attribute with a dedicated header area for meta-data about entire column.

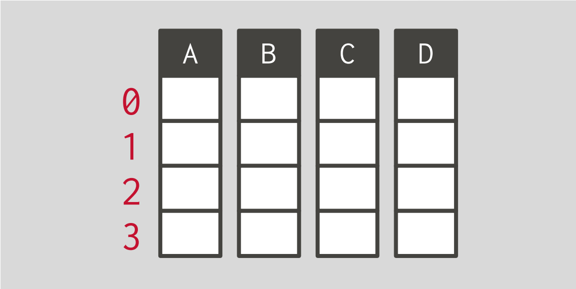


DSM: TUPLE IDENTIFICATION

Choice #1: Fixed-length Offsets

→ Each value is the same length for an attribute. Use simple arithmetic to jump to an offset to find a tuple.

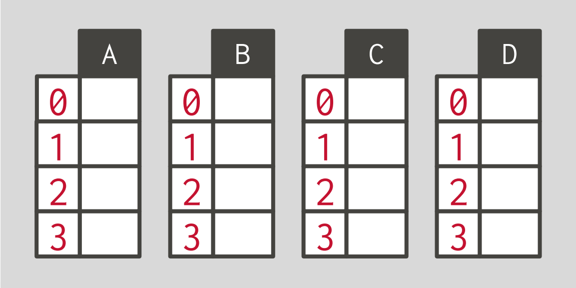
→ Need to convert variable-length data into fixed-length values.



Choice #2: Embedded Tuple Ids

→ Each value is stored with its tuple id in a column.

→ Need auxiliary data structures to find offset within a column for a given tuple id.



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).

Still need to handle semi-structured data…

OBSERVATION

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

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

But the DBMS needs to store data in a columnar format for storage + execution benefits.

We need columnar scheme that still stores attributes separately but keeps the data for each tuple physically close to each other…

PAX STORAGE MODEL

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

→ This is what Paraquet and Orc use.

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

DATA PAGE LAYOUTS FOR RELATIONAL DATABASES ON DEEP MEMORY HIERARCHIES
VLDB JOURNAL 2002

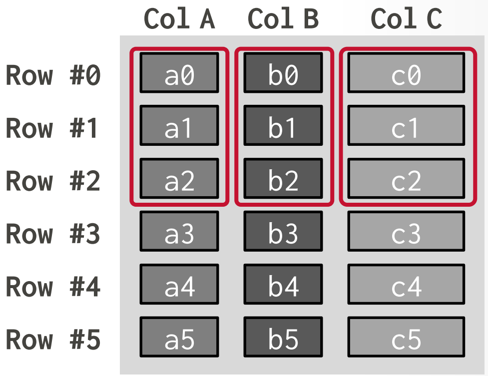
PAX: PHYSICAL ORGANIZATION

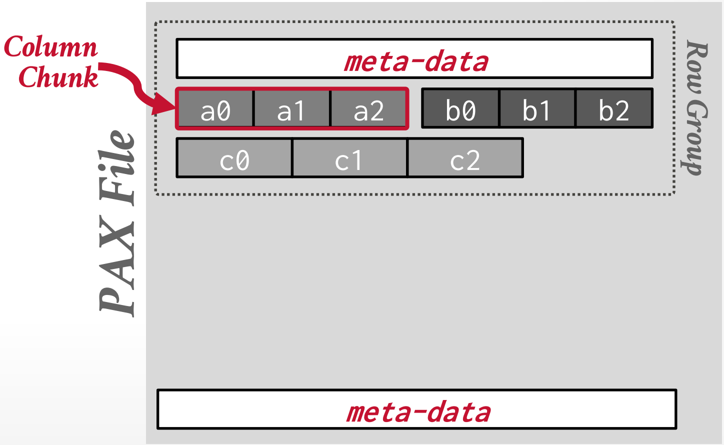
Horizontally partition data into ***row groups***. Then vertically partition their attributes into ***column chunks***.

Global meta-data directory contains offsets to the file's row groups.

→ This is stored in the footer if the file is immutable (Parquet, Orc).

Each row group contains its own meta-data header about its contents.





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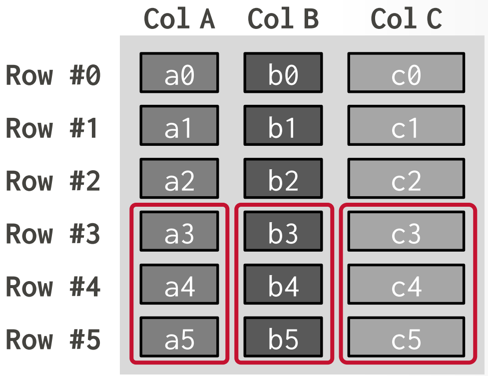
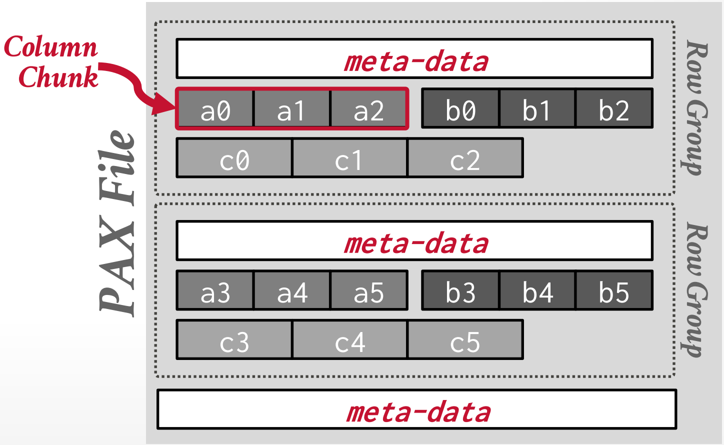




OBSERVATION

Most DBMSs use a proprietary on-disk binary file format for persistent data. The only way to share data between systems is to convert data into a common text-based format

→ Examples: CSV, JSON, XML

There are open-source binary file formats that make it easier to access data across systems and libraries for extracting data from files.

→ Libraries provide an iterator interface to retrieve (batched) columns from files.

OPEN-SOURCE PERSISTENT DATA FORMATS

HDF5 (1998)
→ Multi-dimensional arrays for scientific workloads.

Apache Avro (2009)
→ Row-oriented format for Hadoop that replace SequenceFiles.

Apache Parquet (2013)
→ Compressed columnar storage from Cloudera/Twitter for Impala.

Apache ORC (2013)
→ Compressed columnar storage from Meta for Apache Hive.

Apache CarbonData (2016)
→ Compressed columnar storage with indexes from Huawei.

Apache Arrow (2016)
→ In-memory compressed columnar storage from Pandas/Dremio.

FORMAT DESIGN DECISIONS

File Meta-Data

Format Layout

Type System

Encoding Schemes

Block Compression

Filters

Nested Data

AN EMPIRICAL EVALUATION OF COLUMNAR STORAGE FORMATS
VLDB 2023

A DEEP DIVE INTO COMMON OPEN FORMATS FOR ANALYTICAL DBMSS
VLDB 2023

FILE META-DATA

Files are **self-contained** to increase portability. They contain all the necessary information to interpret their contents without external data dependencies.

Each file maintains global meta-data (usually in its footer) about its contents:
→ Table Schema (e.g., Thrift, Protobuf)
→ Row Group Offsets / Length
→ Tuple Counts / Zone Maps

FORMAT LAYOUT

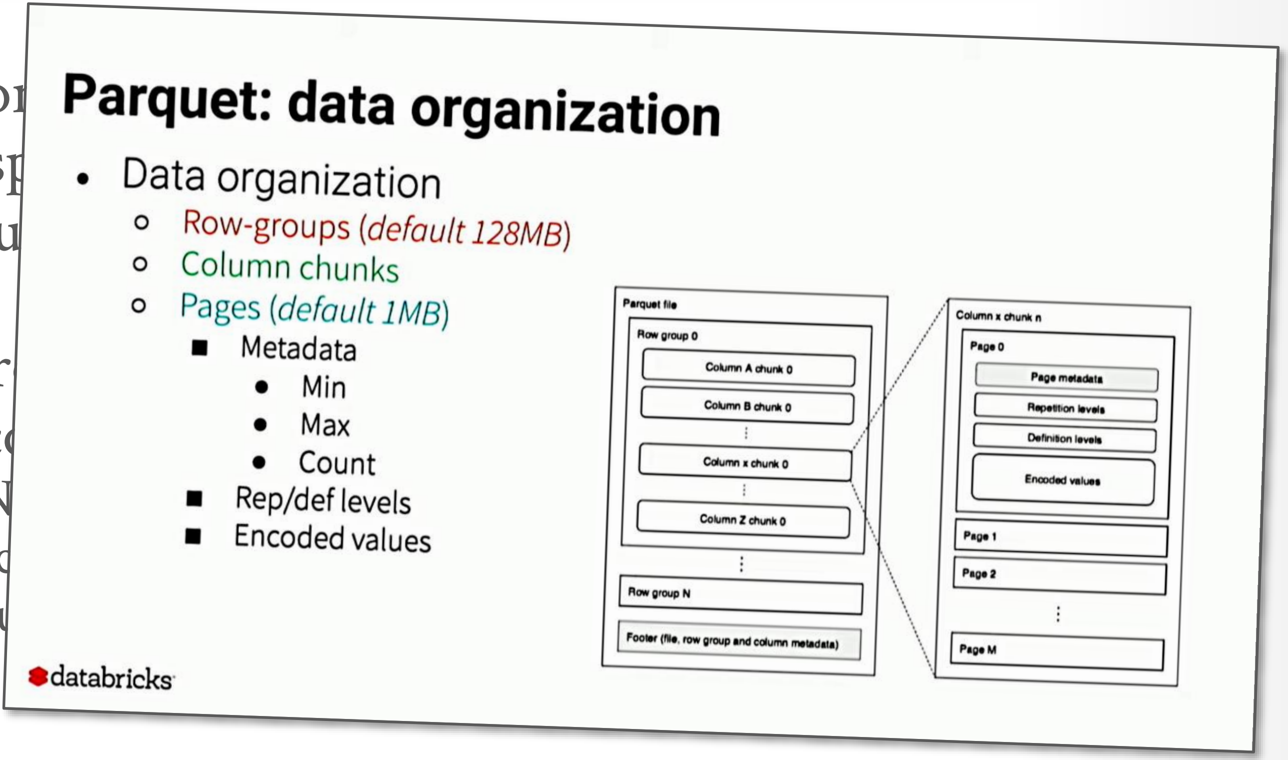
The most common formats use the PAX storage model that splits data row groups that contain one or more column chunks.

The size of row groups varies per implementation and makes compute/memory trade-offs:
→ **Parquet**: Number of tuples (e.g., 1 million).
→ **Orc**: Physical Storage Size (e.g., 250 MB).
→ **Arrow**: Number of tuples (e.g., 1024*1024).

FORMAT LAYOUT

The most co[r]
model that sp
or more colu

The size of r
and makes c
→ **Parquet**: N
→ **Orc**: Physic
→ **Arrow**: Nu



TYPE SYSTEM

Defines the data types that the format supports.

- → **Physical**: Low-level byte representation (e.g., IEEE-754).
- → **Logical**: Auxiliary types that map to physical types.

Formats vary in the complexity of their type systems that determine how much upstream producer / consumers need to implement:

- → **Parquet**: Minimal # of physical types. Logical types provide annotations that describe interpretation of primitive type data.
- → **ORC**: More complete set of physical types.

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Apache Parquet

Documentation / File Format / Types

Types

The types supported by the file format are intended to be as minimal as possible, with a focus on how the types effect on disk storage. For example, 16-bit ints are not explicitly supported in the storage format since they are covered by 32-bit ints with an efficient encoding. This reduces the complexity of implementing readers and writers for the format. The types are:

```
- BOOLEAN: 1 bit boolean
- INT32: 32 bit signed ints
- INT64: 64 bit signed ints
- INT96: 96 bit signed ints
- FLOAT: IEEE 32-bit floating point values
- DOUBLE: IEEE 64-bit floating point values
- BYTE_ARRAY: arbitrarily long byte arrays
- FIXED_LEN_BYTE_ARRAY: fixed length byte arrays
```

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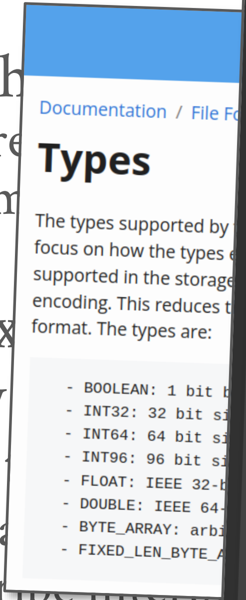

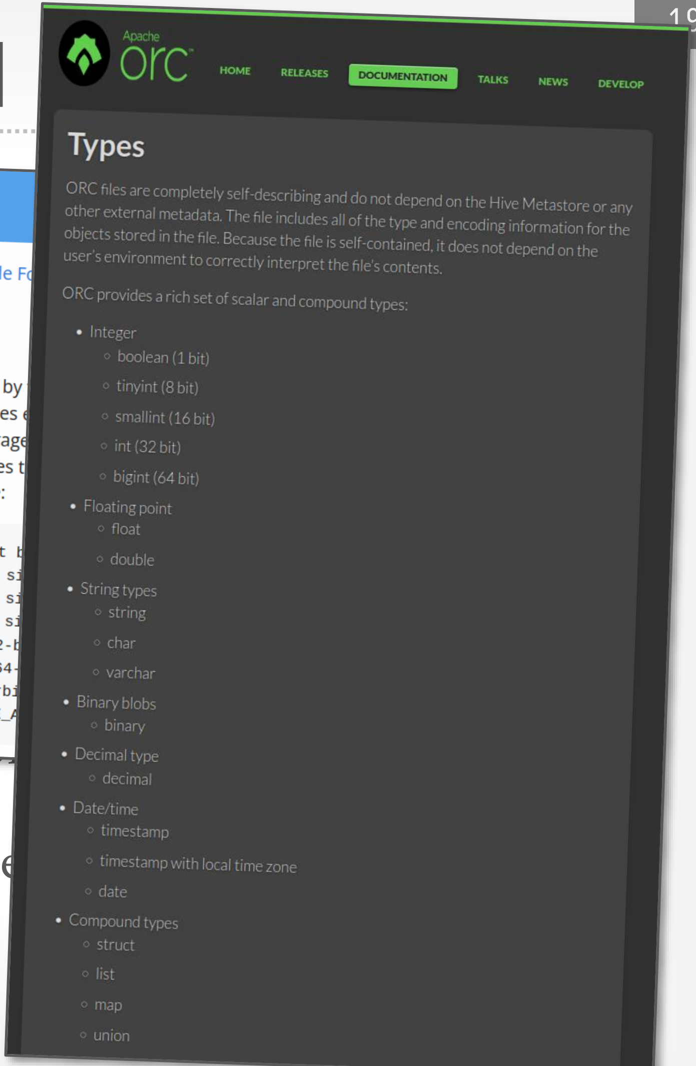

ENCODING SCHEMES

An encoding scheme specifies how the format stores the bytes for contiguous/related data.

→ Can apply multiple encoding schemes on top of each other to further improve compression.

Dictionary Encoding

Run-Length Encoding (RLE)

Bitpacking

Delta Encoding

Frame-of-Reference (FOR)

DICTIONARY COMPRESSION

Replace frequent values with smaller fixed-length codes and then maintain a mapping (dictionary) from the codes to the original values.

→ Codes could either be positions (using hash table) or byte offsets into dictionary.
→ Optionally sort values in dictionary.
→ Further compress dictionary and encoded columns.

Format must handle when the number of distinct values (NDV) in a column chunk is too large.

→ **Parquet**: Max dictionary size (1 MB).
→ **ORC**: Pre-compute NDV and disable if too large.

DICTIONARY COMPRESSION

Original Data

name
William
Andrea
Andy
Matt
Andy
Andy
Andy
Andy

Unsorted Dictionary

len	value
6	Andrea
7	William
4	Andy
4	Matt

pos
1
0
2
3
2
2
2
2

vs.

offset
7
0
13
17
13
13
13
13

Sorted Dictionary

len	value
6	Andrea
4	Andy
4	Matt
7	William

pos
3
0
1
2
1
1
1
1

vs.

offset
14
0
7
11
7
7
7
7

DICTIONARY COMPRESSION

Design Decision #1: Eligible Data Types

→ **Parquet**: All data types
→ **ORC**: Only strings

Design Decision #2: Compress Encoded Data

→ **Parquet**: RLE + Bitpacking
→ **ORC**: RLE, Delta Encoding, Bitpacking, FOR

Design Decision #3: Expose Dictionary

→ **Parquet**: Not supported
→ **ORC**: Not supported

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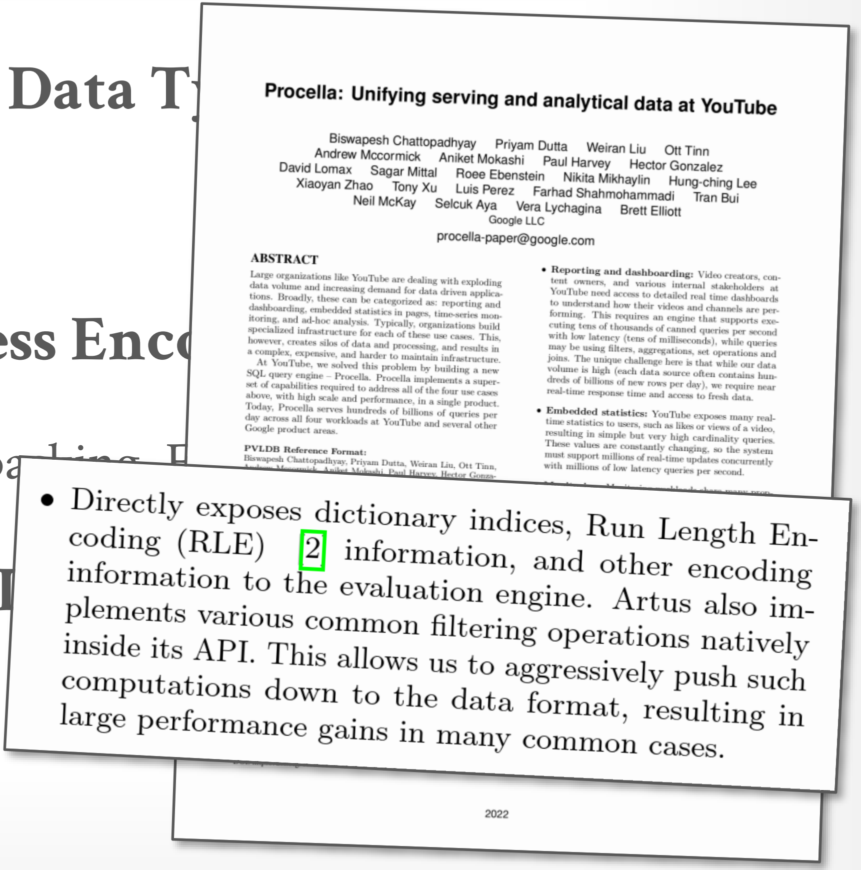

Procella: Unifying serving and analytical data at YouTube

Biswapesh Chattopadhyay Priyam Dutta Weiran Liu Ott Tinn
Andrew Mccormick Aniket Mokashi Paul Harvey Hector Gonzalez
David Lomax Sagar Mittal Roee Ebenstein Nikita Mikhaylin Hung-ching Lee
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ABSTRACT

Large organizations like YouTube are dealing with exploding data volume and increasing demand for data driven applications. Broadly, these can be categorized as: reporting and dashboarding, embedded statistics in pages, time-series monitoring, and ad-hoc analysis. Typically, organizations build specialized infrastructure for each of these use cases. This, however, creates silos of data and processing, and results in a complex, expensive, and harder to maintain infrastructure.

At YouTube, we solved this problem by building a new SQL query engine – Procella. Procella implements a superset of capabilities required to address all of the four use cases above, with high scale and performance, in a single product. Today, Procella serves hundreds of billions of queries per day across all four workloads at YouTube and several other Google product areas.

PVLDB Reference Format:
Biswapesh Chattopadhyay, Priyam Dutta, Weiran Liu, Ott Tinn,

- **Reporting and dashboarding:** Video creators, content owners, and various internal stakeholders at YouTube need access to detailed real time dashboards to understand how their videos and channels are performing. This requires an engine that supports executing tens of thousands of canned queries per second with low latency (tens of milliseconds), while queries may be using filters, aggregations, set operations and joins. The unique challenge here is that while our data volume is high (each data source often contains hundreds of billions of new rows per day), we require near real-time response time and access to fresh data.
- **Embedded statistics:** YouTube exposes many real-time statistics to users, such as likes or views of a video, resulting in simple but very high cardinality queries. These values are constantly changing, so the system must support millions of real-time updates concurrently with millions of low latency queries per second.

- Directly exposes dictionary indices, Run Length Encoding (RLE) [2] information, and other encoding information to the evaluation engine. Artus also implements various common filtering operations natively inside its API. This allows us to aggressively push such computations down to the data format, resulting in large performance gains in many common cases.

2022

BLOCK COMPRESSION

Compress data using a general-purpose algorithm. Scope of compression is only based on the data provided as input.

→ LZO (1996), LZ4 (2011), Snappy (2011), Zstd (2015)

Considerations

→ Computational overhead

→ Compress vs. decompress speed

→ Data opaqueness

FILTERS

Zone Maps:

→ Maintain min/max values per column at the file-level and row group-level.

→ By default, both Parquet and ORC store zone maps in the header of each row group.

Bloom Filters:

→ Track the existence of values for each column in a row group. More effective if values are clustered.

→ Parquet uses Split Block Bloom Filters from Impala.

NESTED DATA

Real-world data sets often contain semi-structured objects (e.g., JSON, Protobufs).

A file format will want to encode the contents of these objects as if they were regular columns.

Approach #1: Record Shredding

Approach #2: Length+Presence Encoding

DREMEL: A DECADE OF INTERACTIVE SQL ANALYSIS AT WEB SCALE
VLDB 2020

NESTED DATA: SHREDDING

Store paths in nested structure as separate columns.

Maintain ***repetition*** and ***definition*** fields as separate columns to avoid having to retrieve/access ancestor attributes.

```
message Document {
  required int64 DocId;
  repeated group Name {
    repeated group Language {
      required string Code;
      optional string Country;
    }
    optional string Url;
  }
}
```

```
DocId: 10
Name:
  Language:
    Code: 'en-us'
    Country: 'us'
  Language:
    Code: 'en'
  Url: 'http://A'
Name:
  Url: 'http://B'
Name:
  Language:
    Code: 'en-gb'
    Country: 'gb'
```

```
DocId: 20
Name:
  Url: 'http://C'
```

DocId

value	r	d
10	0	0
20	0	0

Name.Url

value	r	d
http://A	0	2
http://B	1	2
NULL	1	1
http://C	0	2

Name.Language.Code

value	r	d
en-us	0	2
en	2	2
NULL	1	1
en-gb	1	2
NULL	0	1

Name.Language.Country

value	r	d
us	0	3
NULL	2	2
NULL	1	1
gb	1	3
NULL	0	1

Source: Sergey Melnik

NESTED DATA: LENGTH+PRESENCE

Store paths in nested structure as separate columns but maintain additional columns to track the number of entries at each path level (***length***) and whether a key exists at that level for a record (***presence***).

```
message Document {
  required int64 DocId;
  repeated group Name {
    repeated group Language {
      required string Code;
      optional string Country;
    }
    optional string Url;
  }
}
```

```
DocId: 10
Name:
  Language:
    Code: 'en-us'
    Country: 'us'
  Language:
    Code: 'en'
  Url: 'http://A'
Name:
  Url: 'http://B'
Name:
  Language:
   Code: 'en-gb'
   Country: 'gb'
```

```
DocId: 20
Name:
  Url: 'http://C'
```

DocId

value	p
10	true
20	true

Name

len
3
1

Name.Url

value	p
http://A	true
http://B	true
	false
http://C	true

Name.Language

len
2
0
1
0

Name.Language.Code

value	p
en-us	true
en	true
en-gb	true

Name.Language.Country

value	p
us	true
	false
gb	true

Source: Sergey Melnik

EXPERIMENTAL EVALUATION

Analyze real-world data sets to extract key properties. Then create a microbenchmark to create synthetic data sets and workloads that vary these properties.

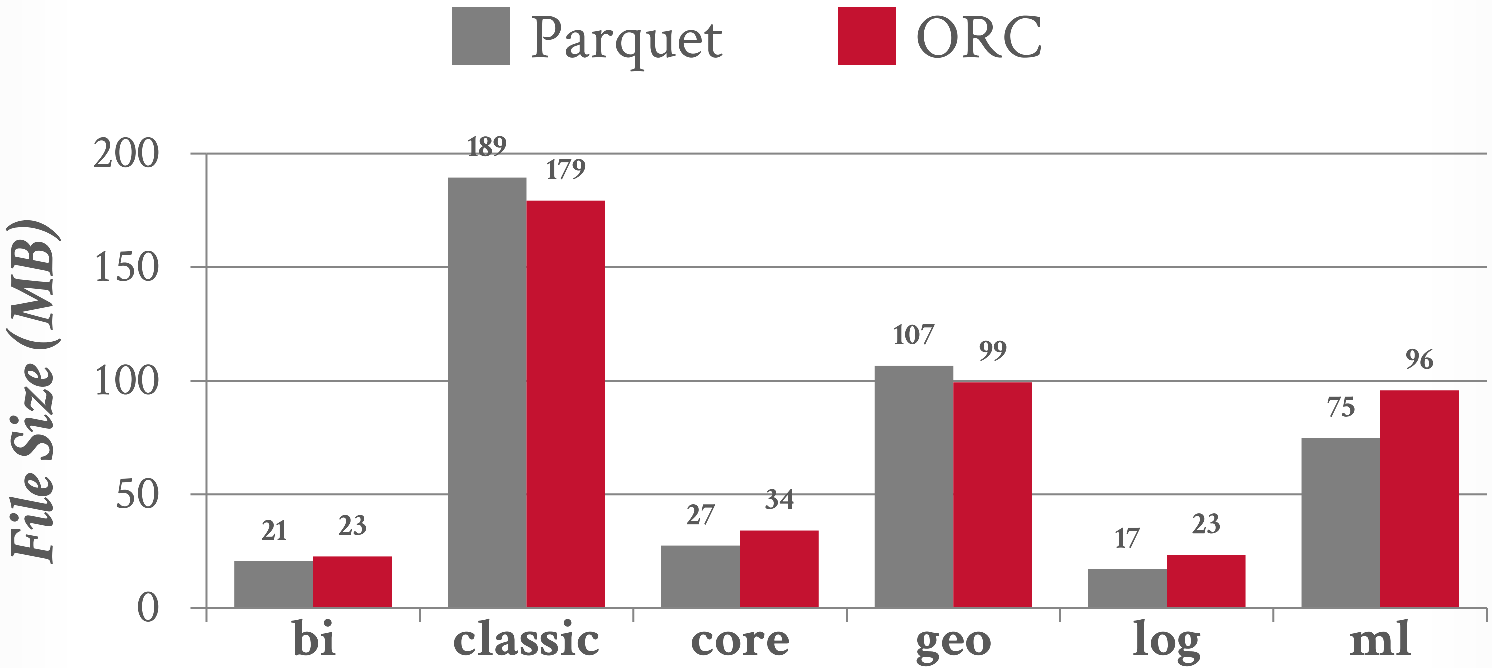
Use Arrow's C++ Parquet/ORC access libraries for most benchmarks.

→ Wildly different completeness / optimizations across implementations.

AN EMPIRICAL EVALUATION OF COLUMNAR STORAGE FORMATS
VLDB 2023

COMPRESSION RATIO

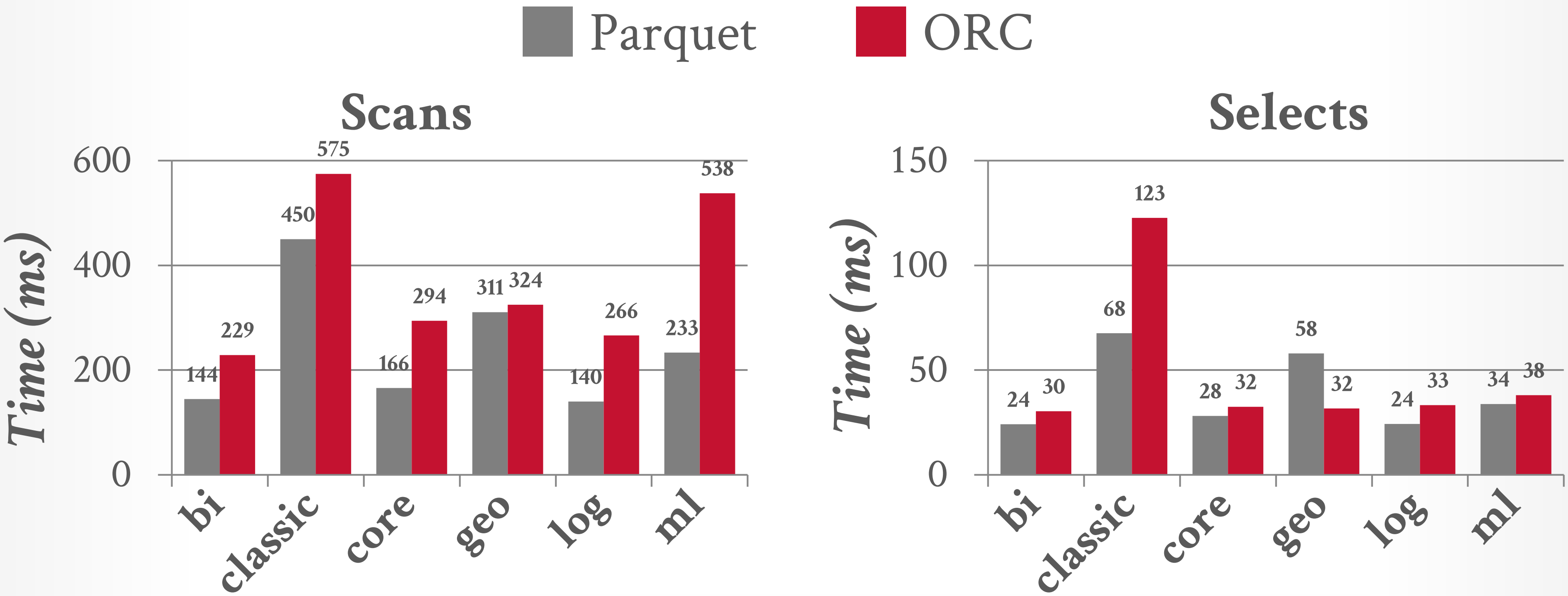
Real-World Data Sets



Source: Xinyu Zheng

DECODING PERFORMANCE

Real-World Data Sets



Source: Xinyu Zheng

LESSONS

Dictionary encoding is effective for all data types and not just strings.

→ Real-world data is repetitive and converting arbitrary data to integers in a small domain enables better compression.

Simplistic encoding schemes are better on modern hardware.

→ Determining which encoding scheme a chunk is using at runtime causes branch mispredictions.

Avoid general-purpose block compression.

→ Network/disk are no longer the bottleneck relative to CPU performance.

Source: Xinyu Zheng

PARTING THOUGHTS

Hardware has changed in the last 10 years that we need to reassess how a DBMS should store data.

Although widely successful and deployed, there are several deficiencies with Parquet/ORC.

→ No statistics (e.g., histograms, sketches).
→ No incremental schema deserialization.
→ Numerous implementations of varying completeness.

NEXT CLASS

Better encoding schemes