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 bring data to mem before execute -> executor get data from block in mem

Parallelization

Clustering / Sorting indentify data sort close to each other

Late Materialization

The difference is that a materialized view is an actual copy of the query results, written to disk, whereas a virtual view is just a shortcut for writing queries. When you read from a virtual view, the SQL engine expands it into the view's underlying query on the fly and then processes the expanded query.
- In Progres: can manual refresh khi data change

Materialized Views / Result Caching tinh toan trc 1 phan du lieu/query hay dung
A common special case of a materialized view is known as a data cube or OLAP cube

Data Skipping

Data Parallelization / Vectorization can use SIMD to do multiple process

Code Specialization / Compilation can generate C code to run

SEQUENTIAL SCAN OPTIMIZATIONS

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

TODAY'S AGENDA

Storage Models

Persistent Data Formats

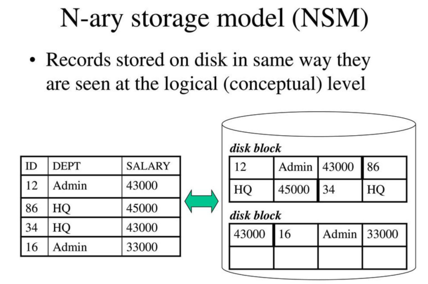
STORAGE MODELS

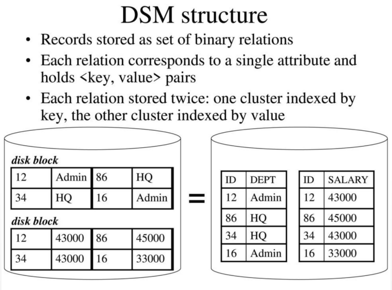
A DBMS's ***storage model*** specifies how it physically organizes tuples on disk and in memory.

Choice #1: *N*-ary Storage Model (NSM) default, most use

Choice #2: Decomposition Storage Model (DSM)

Choice #3: Hybrid Storage Model (PAX) better locality





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)

NSM can not bring partial pages -> only bring whole page , because need header,...

-> not suitable for OLAP workload
E.x: page have 100 cols, we need 4 , but need to fetch all 100 cols

DECOMPOSITION STORAGE MODEL (DSM)

column

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***.

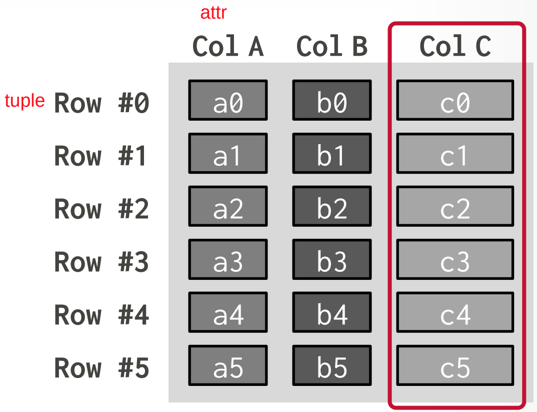
in file, we also break in smaller chunks

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

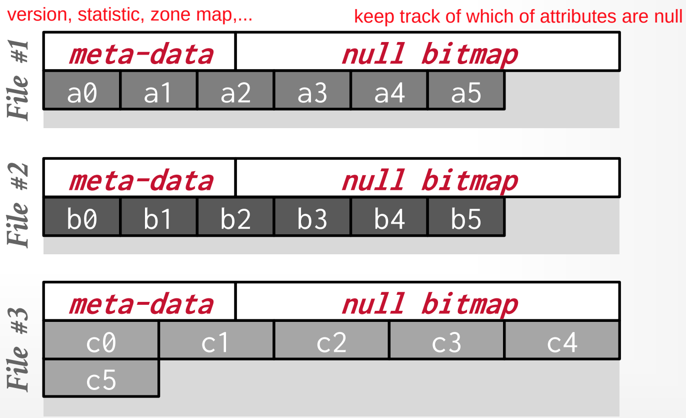
DSM: PHYSICAL ORGANIZATION

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.

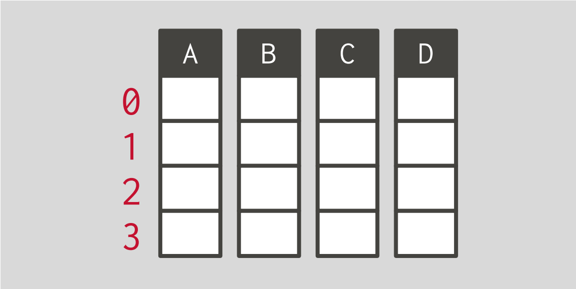


DSM: TUPLE IDENTIFICATION

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.

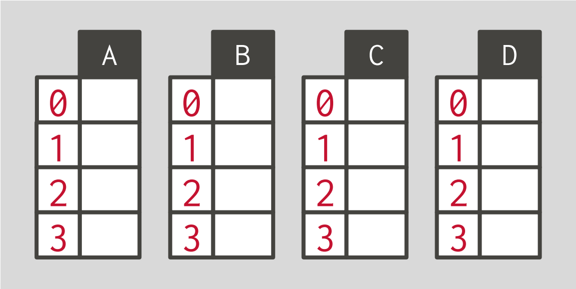


Choice #2: Embedded Tuple Ids

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

phụ trợ

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

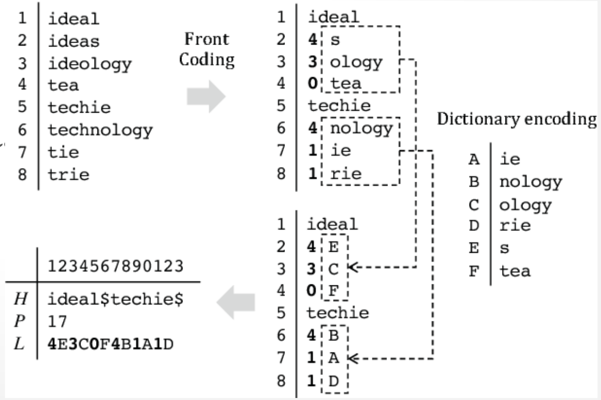


DSM: VARIABLE-LENGTH DATA

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.

Cần kết hợp cả columna với row-base

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 faster processing on columnar storage while retaining the spatial locality benefits of row storage.

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

PAX: PHYSICAL ORGANIZATION

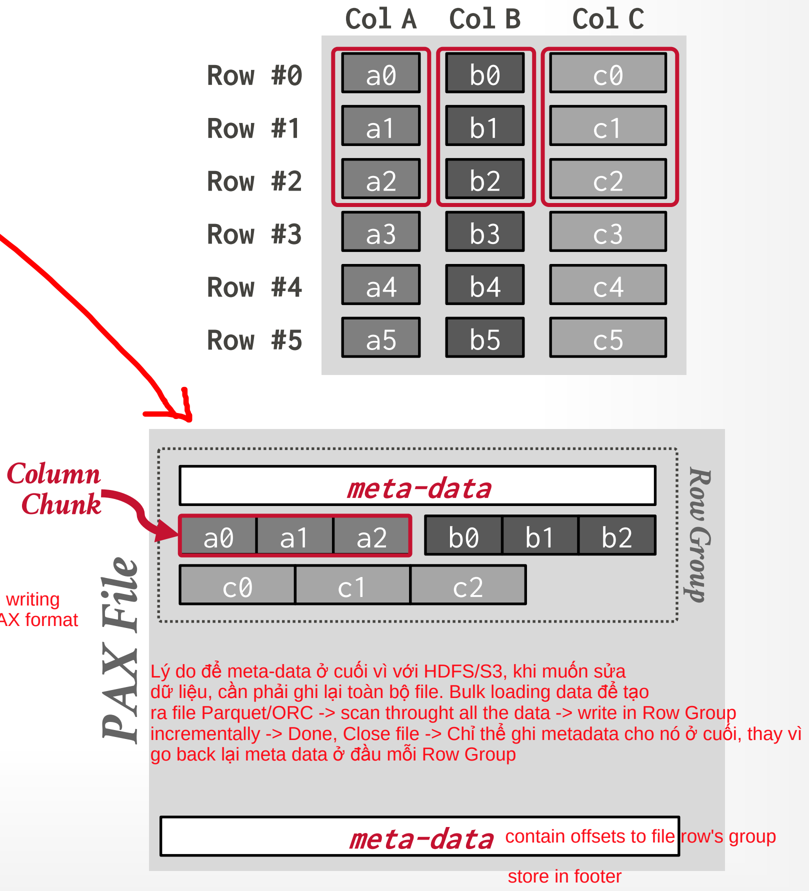
Horizontally partition data into ***row groups***. Then vertically partition their attributes into ***column chunks***.

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).

PAX File
~ version of piece data of tuples, writing sequentially and organizing in PAX format

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



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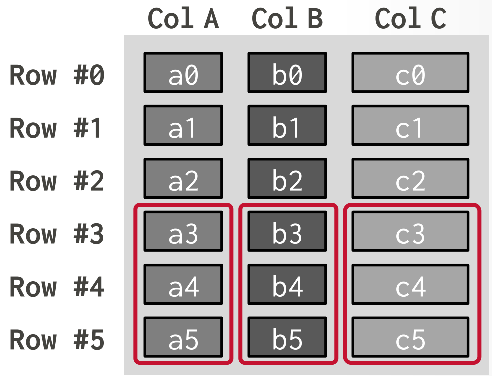
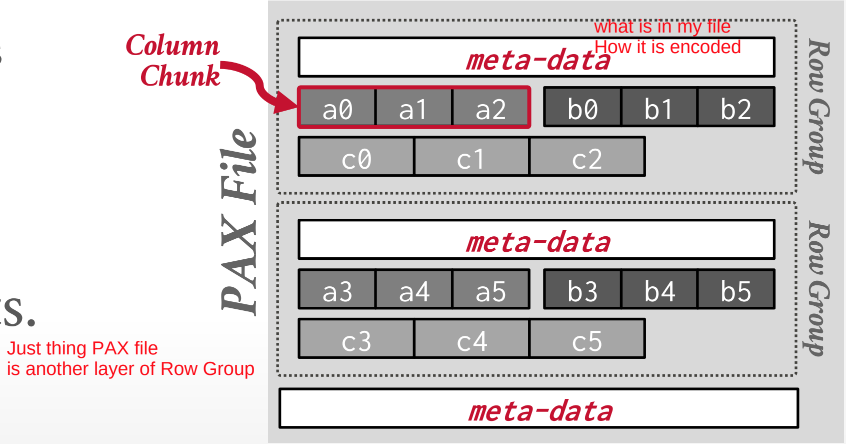




OBSERVATION

ngoại trừ DuckDB

độc quyền

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

The only way to move data from one system to another
sql.dump()

worst (all data decode to ASCII)

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 cung cấp interator interface để truy cập các cột từ file

OPEN-SOURCE PERSISTENT DATA FORMATS

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

Apache Avro (2009) at that time, even columna exist Hadoop still write and process in row --> Stuck
→ Row-oriented format for Hadoop that replace SequenceFiles. k,v pair

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

Apache ORC (2013)
→ Compressed columnar storage from Meta for Apache Hive.
convert sql to map-reduce job

Apache CarbonData (2016)
→ Compressed columnar storage with indexes from Huawei. add additional metadata to keep track schema version

Apache Arrow (2016) ~ In memory version of Parquet
→ In-memory compressed columnar storage from Pandas/Dremio.
allow to change data btw different process/network

class nay tap chung vao Parquet, ORC

kiểu SQL có nhiều vấn đề, nhưng sẽ ko đi đâu, vì nó đc sử dụng rộng rãi

FORMAT DESIGN DECISIONS

File Meta-Data

Format Layout

Type System

Encoding Schemes

Block Compression

Filters

Nested Data

Parquet has some problem, found when develop Arrow

AN EMPIRICAL EVALUATION OF COLUMNAR STORAGE FORMATS
VLDB 2023

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

FILE META-DATA

tính di động

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:

define schema -> it have a way to generate a binary encoding for this, and embed it in the metadata file
Problem
- If have table with 1000 cols, and only need 2 cols, we have to deserialize the entire binary code

→ Table Schema (e.g., Thrift, Protobuf)

Flatbuf (tu Goofle) la verision moi

directly tell us how to jump in the file
to find the begining of row group

→ 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).

```
>>> print(pd.concat(all_results, ignore_index=True).to_string(index=Fa
              parquetFile  iterations  total   avg   min   max  stdev
 data/players_10k.parquet          10  0.963 0.096 0.092 0.120  0.009
data/players_100k.parquet          10  0.122 0.012 0.011 0.015  0.001
  data/players_1m.parquet          10  0.017 0.002 0.001 0.003  0.000
 data/players_10m.parquet          10  0.013 0.001 0.001 0.001  0.000
>>> con.execute("""
... select file_name, count(distinct row_group_id)
... from parquet_metadata('data/*.parquet')
... group by all
... """).fetchdf()
                  file_name  count(DISTINCT row_group_id)
0   data/players_10k.parquet                          977
1    data/players_1m.parquet                           10
2  data/players_100k.parquet                          100
3   data/players_10m.parquet                            2
```

Parquet write

a1b1c1
a2b2c2
->
(in mem)
Column Store A , CS B, CS C
-> 100 rows + raw data > page size (1MB)
(in mem)
Page Store A, PS B, PS C (đã nén)
-> raw data in CS + compress data in PS > block size
(Compressed blockA,B,C) -> ghi ra disk
(Column Store A,B,C) -> ghi ra file

Coi nó như là 1 maximize value để có thể dùng vectorized processing
- Luôn đủ data để cho vào SIMD lanes hay multiple threads process
Ví dụ: Nếu có 1 bảng rất nhiều cột, 1 RG chỉ có 4 tuple

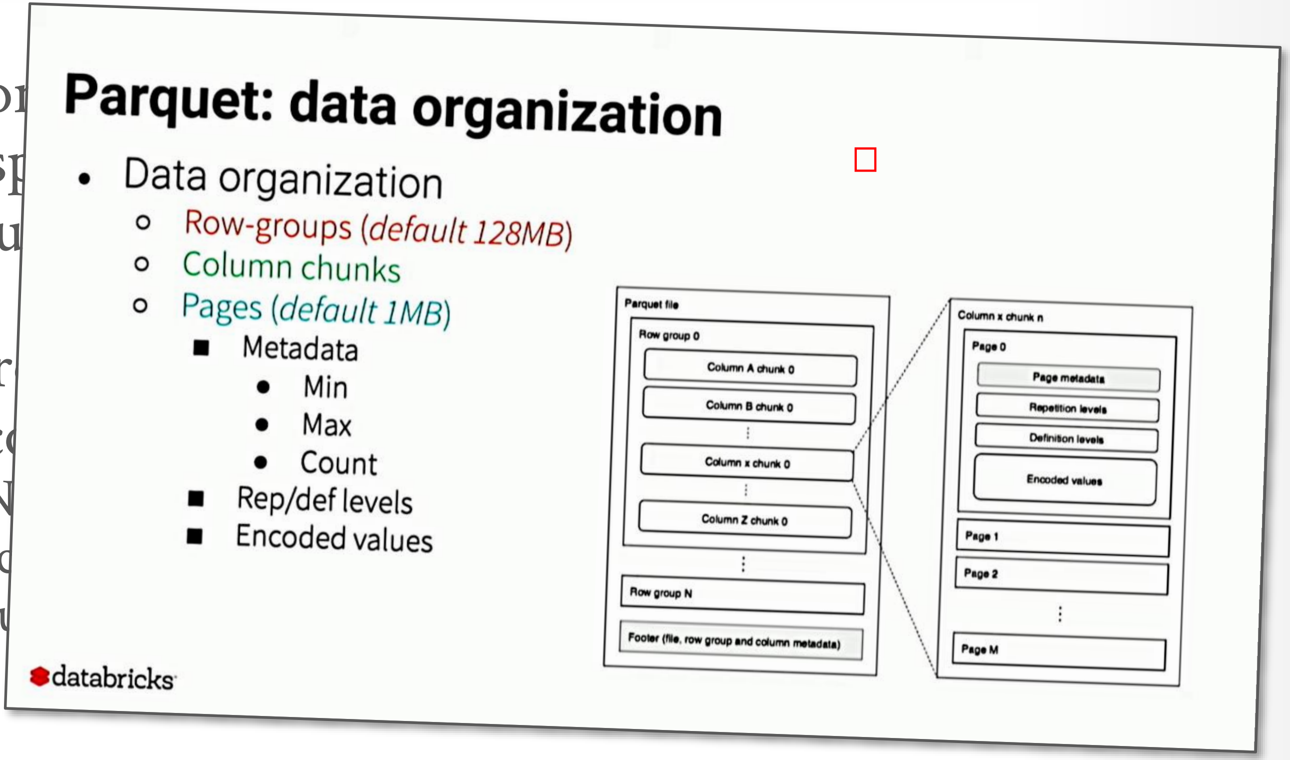
SIMD lanes (na ná bus), nghĩ đơn giản nó là sử lý multiple thread
- đừng nghĩ là 1 thread làm 1 oprerator cho 1 page
- nghĩ nó là sẽ có 1 IO sheduler, tôi cần file này, go get blocks in.
Coordinator : 1 thread xử lý phần đầu, 1 thread xử lý phần sau -> enought work for every one can do

Khi lấy file ở S3, ko lấy toàn bộ PAX file
- Đọc fooder, get metadata , biết được Row Group nào
- Nếu Zone maps được chọn đủ -> ko cần chọn this RG, that RG, let me go get the bite ranges that I need

FORMAT LAYOUT

The most co[…]
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.

TYPE SYSTEM

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Apache Parquet

Documentation / File Format / Types

Types

sẽ có trường hợp số nhỏ
và sử dụng int64 sẽ thừa nhiều số 0 ở sau

Nhưng ko sao, vì đằng nào nó cũng được compress

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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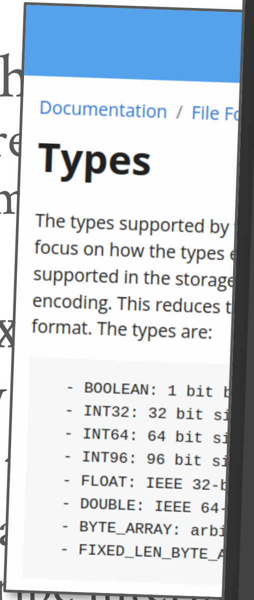
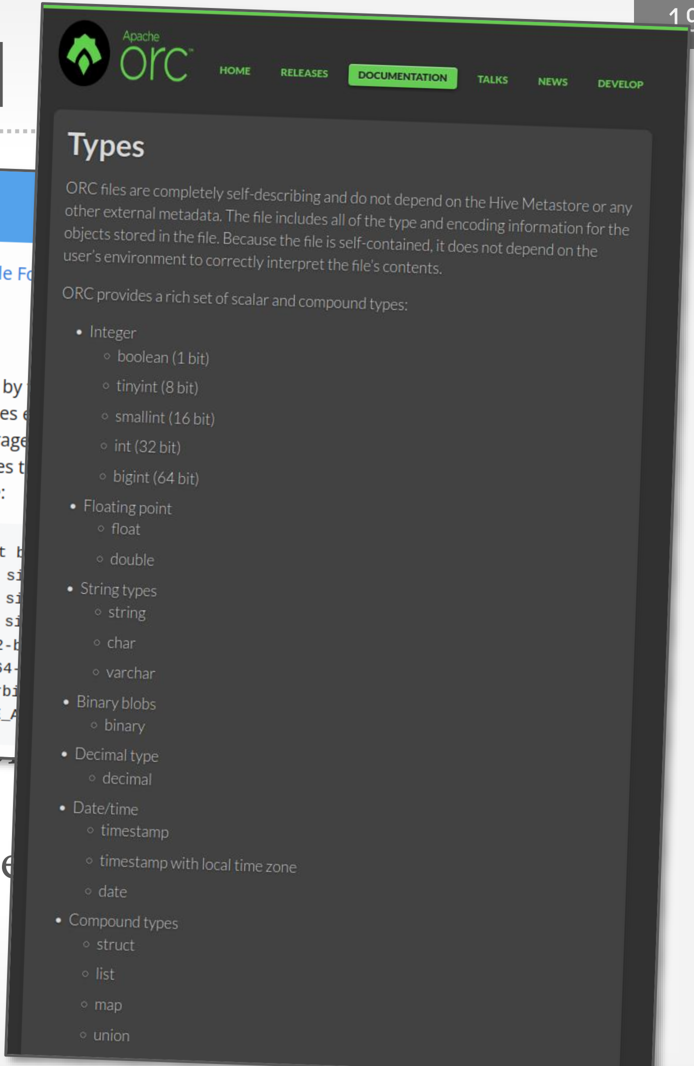


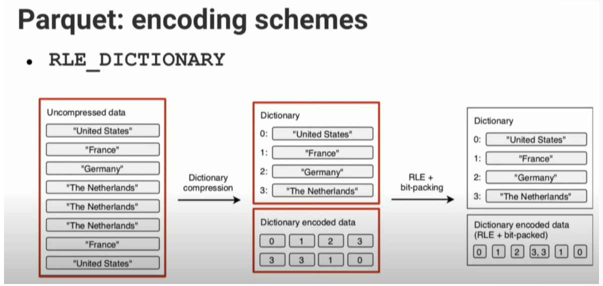


ENCODING SCHEMES

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.

RLE_DICTIONARY
= RLE + bit-packing + dict compression



base, nhưng cái khác sẽ compress tiếp dựa vào output cái này

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). khi data ko phù hợp để dict encoding -> dừng encode
→ **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
0	6	Andrea
1	7	William
2	4	Andy
3	4	Matt

	pos		offset
William	1		7
	0		0
	2		13
	3	*vs.*	17
	2		13
	2		13
	2		13
	2		13

nhìn vào bite thứ 7 của dictionaty
nó là starting point
-> ko cần maintain hashtable

Sorted Dictionary

len	value
6	Andrea
4	Andy
4	Matt
7	William

pos		offset
3		14
0		0
1		7
2	*vs.*	11
1		7
1		7
1		7
1		7

DICTIONARY COMPRESSION

data type có thể compress

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

vì nó còn support cả int8

Design Decision #3: Expose Dictionary

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

có thể expose nó ra ngoài file format ?

VD: select count(*) from table where name = 'Andy'
nếu có expose, chỉ cần check Andy có trong Dict

Nếu không câu query ra qua lib, un-compress data , kiếm kết quả, r gửi trả mình

DICTIONARY COMPRESSION

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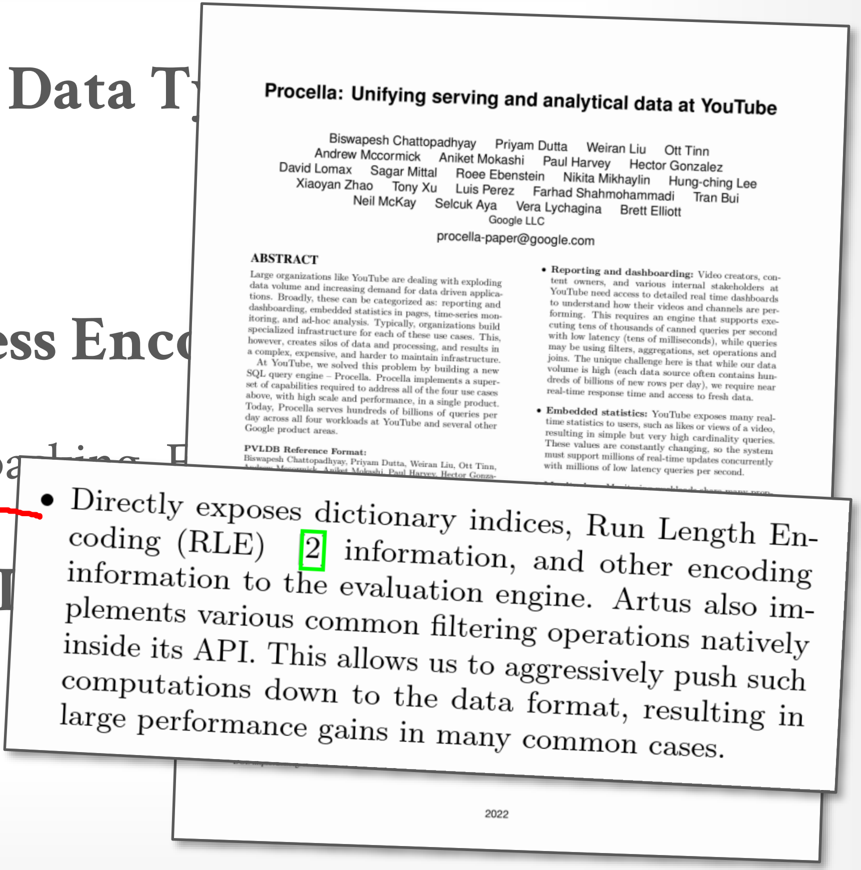


Procella: Unifying serving and analytical data at YouTube

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, Xiaoyan Zhao, Tony Xu, Luis Perez, Farhad Shahmohammadi, Tran Bui, Neil McKay, Selcuk Aya, Vera Lychagina, Brett Elliott
Google LLC
procella-paper@google.com

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

take bloacks the row groups and run and compress it

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)

this make sense in 2014 vì disk/network slow, khi ta có thể reduce data ta đọc từ disk lên mem, và trade-off vs CPU để decompress

Nhưng h thì khác (2024) , CPU lại chậm hơn

Considerations

→ Computational overhead
→ Compress vs. decompress speed
→ Data opaqueness

FILTERS

2 types of Filter

index: tell something exits
filter: tell something can exis, chứ không nói nó exis ở đâu

Zone Maps:

nếu value trong range này, -> nó tồn tại, nhưng không biết ở đâu, cần scan để tìm (B-tree: nó ở offset này, nhưng ko care cụ thể node nào)

→ 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.

Cho zone map
Vì nếu cluster, range will be smaller. Vì nếu từ 0-> infinity, nó sẽ vô dụng

Bloom Filters:

nó là probalistic (đúng đắn) data structure, có thể cho ta biết cái gì might exist, nhưng không thể cho ta biết cái gì không exist
(can get False positives but not false negatives)

→ 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 tốt hơn Approach 2

ORC dùng

Approach #2: Length+Presence Encoding

Dremel: internal name of Big Query

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

NESTED DATA: SHREDDING

idea:
Instead of storing semi-structure as a single block column, then, have to parse every single time when processing

--> split it up, so that every level in path is now treated as a seperate column

Store paths in nested structure as separate columns.

sự lặp

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

nếu ko tồn tại
ở tupple nào -> false

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

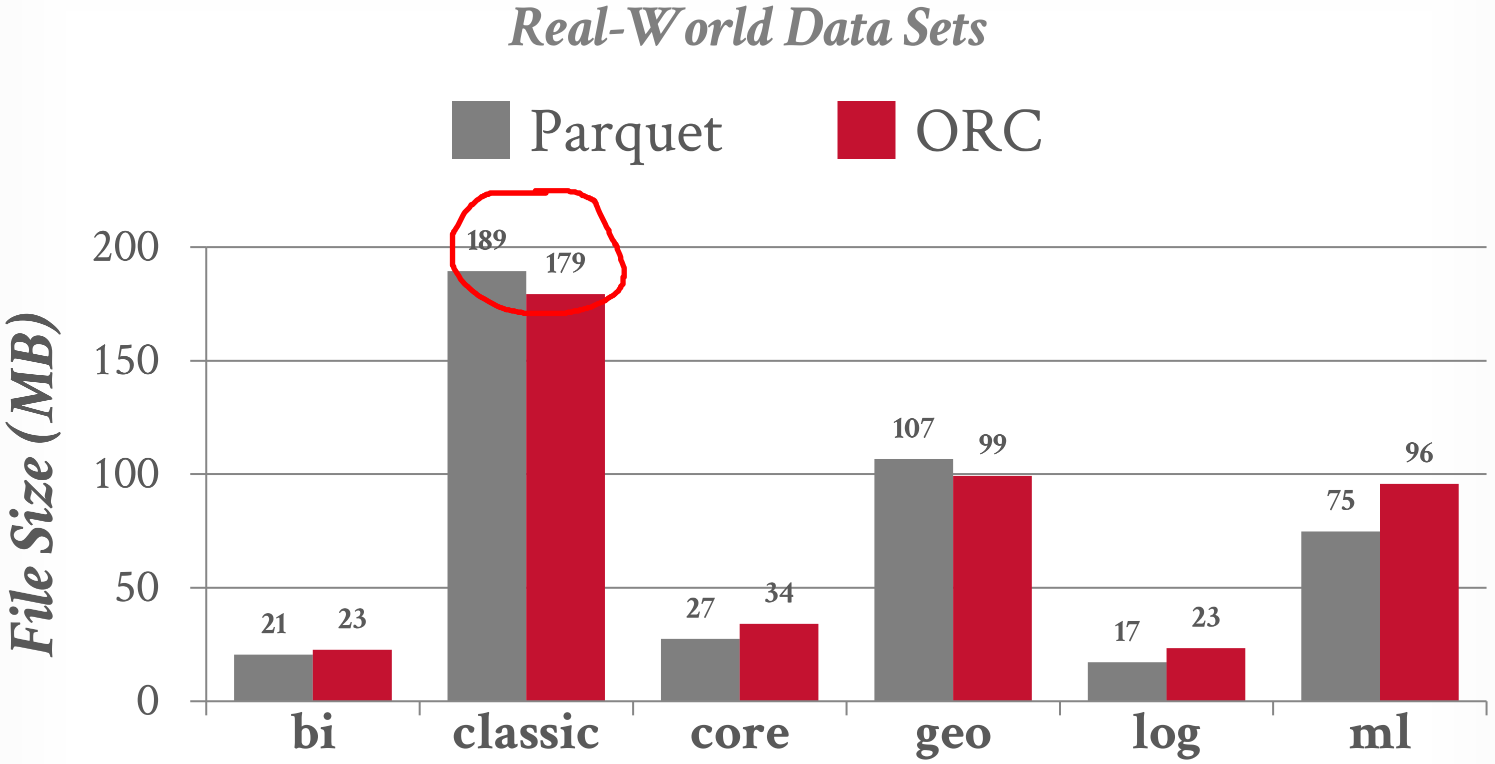
Analyze real-world data sets to extract key properties. Then create a microbenchmark to create synthetic data sets and workloads that vary these properties.

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

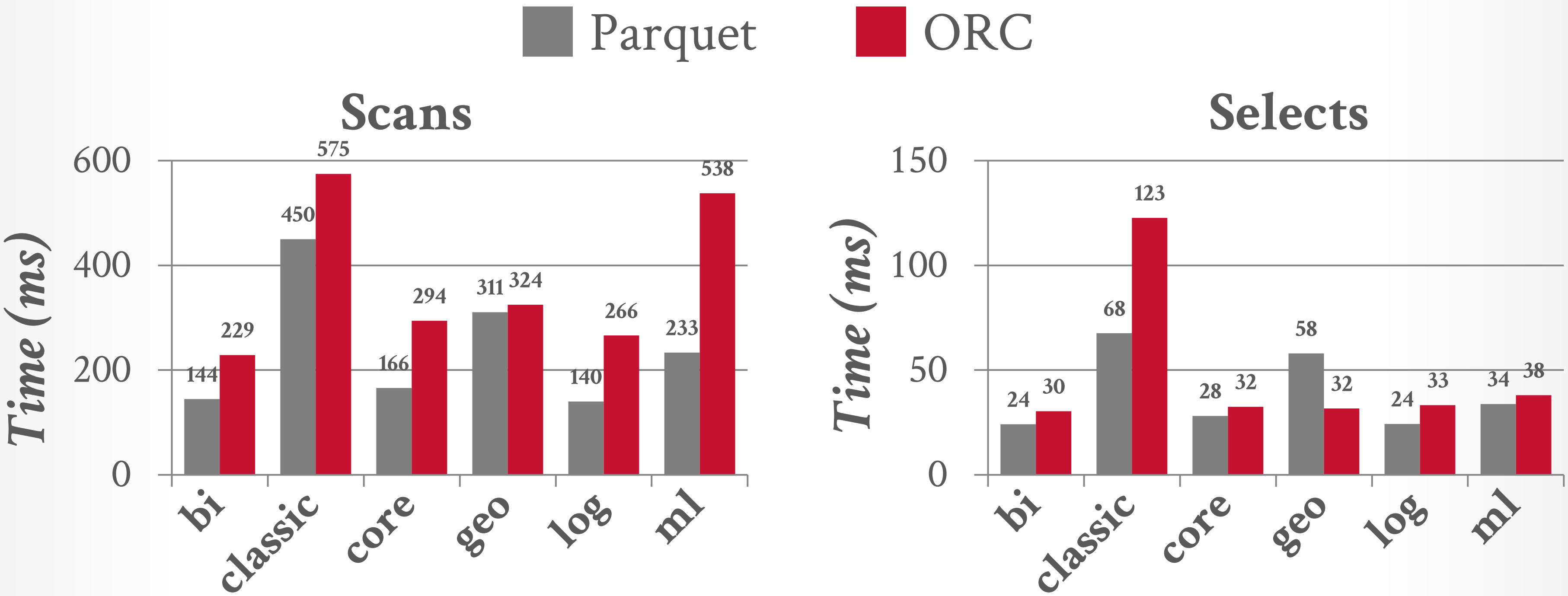
COMPRESSION RATIO



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.

Đơn giản

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. schema version
→ Numerous implementations of varying completeness.

NEXT CLASS

Better encoding schemes