

ADOPTING CLICKHOUSE @ YOUR WORK

MASTER THE FUNDAMENTALS AND BEYOND

INTRODUCTION

Senior Data Engineer.

I have worked in constructing real-time data pipelines, implementing MLOPS architectures, and ensuring data security at scale.

Currently at Earnin, I focus on empowering teams to turn complex data into actionable insights by leveraging modern lakehouse architectures and distributed computing frameworks.

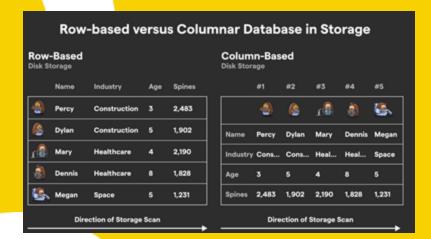






OLAP VS OLTP



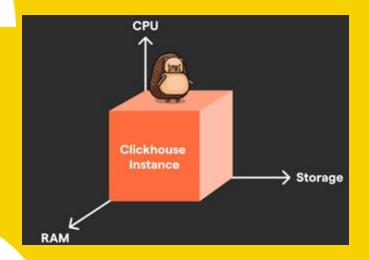






CH VS POSTGRES



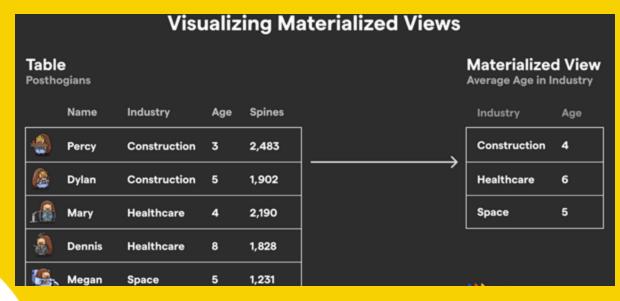






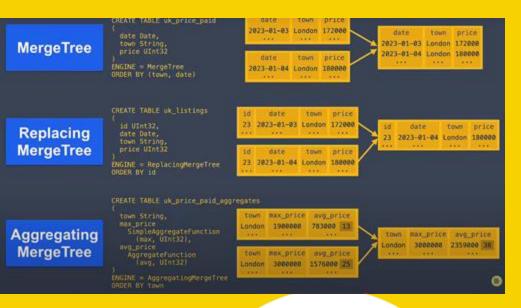
CH VS POSTGRES







ADOPTING CLICKHOUSE @ YOUR WORK



MERGETREE



Parts:

- Data is stored in immutable directories
- sorted by the ORDER BY clause.
- Each part contains compressed column files and a sparse primary index.

Granules: Rows are grouped into granules (size set by index_granularity, default 8192). The sparse index stores marks pointing to the start of each granule.

Merging: Small parts are merged into larger ones (like merge sort) to optimize storage and query efficiency.



MERGETREE

```
SELECT
toStartOfDay(timestamp),
event,
sum(metric_value) as total_metric_value
FROM sensor_values
WHERE site_id = 233 AND timestamp > '2010-01-01' and timestamp < '2023-0
GROUP BY toStartOfDay(timestamp), event
ORDER BY total_metric_value DESC
LIMIT 20
```

```
ReadFromMergeTree

Header: and(greater(timestamp, '2010-01-01'), less(timestamp, '2023-01-0 timestamp DateTime site_id UInt32 event String metric_value Int32

Indexes:

PrimaryKey

Keys:

site_id

toStartOfDay(timestamp)

Condition: and(and((toStartOfDay(timestamp) in (-Inf, 1672531200]), Parts: 2/2

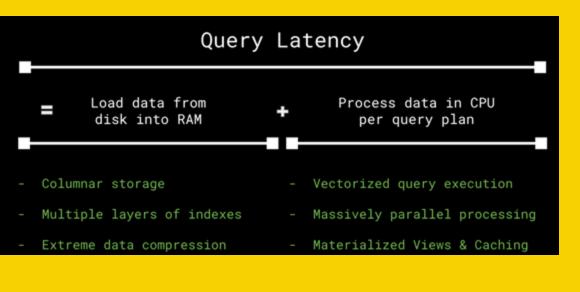
Granules: 11/24415
```

Data is expensive to update

- Scan all the data to find what parts contain the relevant data.
 This isn't often covered by ORDER BY and thus quite expensive.
- Rewrite the whole part (including any columns)
- Ways to handle this:
 - Writing duplicated rows for new data, using other table engines (e.g. Replacing MergeTree) and accounting for this duplication in our queries.



Why CH is so Fast?



```
SELECT Column_a, SUM (Column_b) AS
Column_b_sum, MEDIAN (Column_3) AS
Column_c_median
FROM Table 1
WHERE Column x >= XX AND Column x
<= YY
GROUP BY (Column a)
ORDER BY (Column b)
LIMIT 1000
  Selected Columns
```

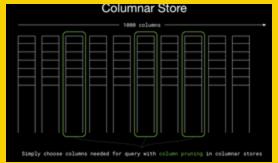
aggregations

groupings

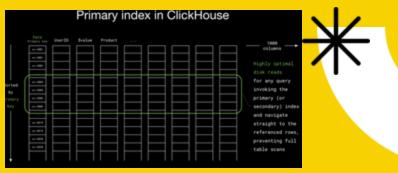
WHERE to select requisite rows

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Load data from disk into RAM



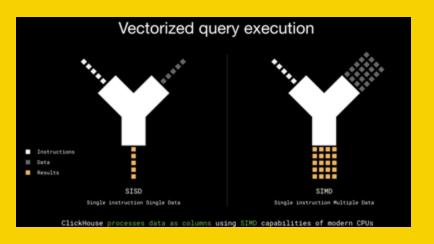


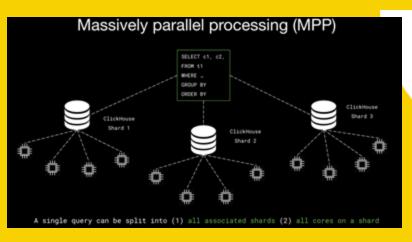


- ClickHouse uses columnar storage to identify precisely the queryrelevant columns,
- multiple layers of indexes to identify precisely the query-relevant rows,
- advanced compression techniques on columnar storage format to minimize size of the data read from disk.



Process Data in CPU





- Vectorized query execution reduces CPU cache miss rates, utilizes the SIMD (single instruction multiple data)
 capabilities of modern CPUs.
- Not only can a single large query be split into the various CPU cores of a single node, but a single query can also leverage all the other CPU cores and disks corresponding to all the other shards in the cluster.
- Materialised views



USE CASE 1: WORKING WITH JSON IN CLICKHOUSE



- True Columnar Storage: JSON paths are stored in a columnar format, enabling optimal compression and vectorized operations.
- Dynamic Data Types: Supports mixed and dynamically changing data types for the same JSON path.
- Dense Storage: Avoids redundant storage of NULL/default values, ensuring scalability for PB-scale datasets.

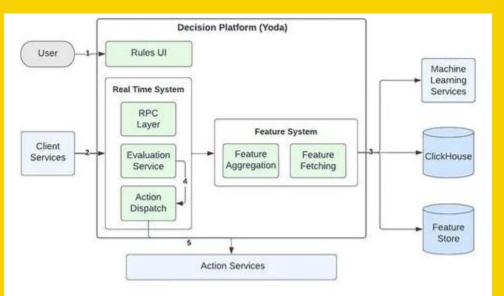
QUERY PATTERNS

- Extracting All Paths and Types: Extract metadata about JSON paths and their types efficiently
- Structured Querying and filtering nested fields: Query specific JSON paths with ease and filter rows based on specific JSON values
- JSON Type Declaration:

```
<column_name> JSON(
    max_dynamic_paths=N,
    max_dynamic_types=M,
    some.path TypeName,
    SKIP path.to.skip,
    SKIP REGEXP 'paths_regexp'
```

USE CASE 2: REAL-TIME RULE ENGINES,

FLOW



WORKFLOW

- Data Ingestion: Real-time data from PostgreSQL and event streams is ingested using Kafka and Flink.
- Feature Engineering: Analysts define dynamic SQL-based features using YAML configurations.
- Rule Evaluation: Features are evaluated against rules, triggering actions such as warnings, suspensions, or account blocks.
- If pos amt exceeds a threshold, flag the transaction.
- Actions include warnings, suspensions, or account blocks

```
Features:
- Name: pos_amt
Type: FLOAT

Query: |

Example CTAINL Configuration:
order_id,
SUM(amount) AS pos_amt
FROM transactions
WHERE created_at >= NOW() - INTERVAL 1 HOUR;
```

COMPARING THE ALTERNATIVES

CLICKHOUSE VS LSM-BASED SYSTEMS

Aspect	ClickHouse (MergeTree)	LSM-Based Trees(Cassendra
Write Path	Direct to disk; sorting by PIDX (batching). Lighter on memory	WAL → in-memory sorting → disk. Memory Intensive
Ingestion Pattern	Prefers larger batches (e.g., 1k rows).Think of this as delayed data freshness	Prefers smaller, frequent writes
Indexing	Sparse primary_idx and column.mrk.	Bloom filters and indexes for SSTables.
Point Queries	Scans excess data; less optimal.	Minimal data scans; highly efficient.
Analytical Queries	Best for aggregations and range scans.	Less optimized compared to columnar storage.
Storage Format	True columnar; efficient compression/vectorization.	Row-oriented; less compression-friendly.



CLICKHOUSE VS APACHE PINOT

Aspect	Apache Pinot	ClickHouse
Data Format	Row-oriented for real-time, columnar for offline.	True columnar format always.
Ingestion Latency	Near real-time with consuming segments.Memory Intensive	Batch ingestion; less optimal for frequent small updates.
Use Case Examples	Real-time dashboards, ad-tech, streaming event analytics.	Batch analytics, log aggregation,

READY TO USE?





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