OPERATING PETABYTE-SCALE ClickHouse CLUSTERS

A Production Engineering Guide from Architecture to Operations

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A Production Engineering Guide from Architecture to Operations

This book is a comprehensive, technically rigorous guide for designing, deploying, and operating ClickHouse clusters at petabyte scale. It covers everything from internal architecture through production engineering, including data modeling, distributed topology design, high-throughput ingestion, query optimization, resource management, Kubernetes deployments, observability, disaster recovery, and cost optimization. Every concept is grounded in the mechanics of how ClickHouse actually works, with concrete numbers, working configuration examples, and real-world architectural patterns drawn from production deployments. The material assumes you are an experienced engineer who already knows SQL and database fundamentals and needs to run ClickHouse reliably in production at scale.

Introduction

A logging pipeline that ingests fifty million events per minute. A real-time fraud detection system scoring transactions in under fifty milliseconds across billions of historical records. An observability platform holding petabytes of traces and metrics with sub-second query latency for on-call engineers debugging production incidents. These are not hypothetical scenarios or marketing examples. They are daily workloads running on ClickHouse clusters at companies like Netflix, Uber, PostHog, and countless others that depend on this database to make real-time decisions.

If you are reading this book, you are likely facing a problem that ClickHouse exists to solve. Your OLTP databases are too slow for analytical queries. Your data warehouse costs are exploding. Your streaming pipelines have too much latency for the real-time dashboards your users demand. You have heard that ClickHouse is incredibly fast and are considering it for production. Or perhaps you already run ClickHouse and are hitting limits, and you need to scale further without losing reliability or sanity.

Either way, you face the same fundamental challenge: ClickHouse performs brilliantly when configured correctly and abysmally when it is not. The gap between good and bad performance is not marginal. It is measured in orders of magnitude. A query that runs in two seconds with the right schema can take twenty minutes with the wrong one. A cluster that handles millions of rows per second with proper ingestion patterns can choke on a few thousand. A deployment that survives node failures gracefully can lose data when replication is misconfigured.

This book exists to close that gap. It is not a tutorial that walks you through your first INSERT statement. It is a production engineering reference for people who must design systems that stay up when things go wrong, that scale as data grows, that meet latency requirements under load, and that do not cost an arm and a leg to operate.

What This Book Covers

The chapters are organized as a progression from foundational understanding through advanced production engineering. The first section covers the architectural foundations: what ClickHouse is and is not, how the columnar storage engine works, how MergeTree stores and merges data, and how queries are actually executed. Understanding these internals is not academic. It directly informs every design decision you make, from how you choose partition keys to how you size your cluster.

The second section covers data modeling, which is the single most important factor in ClickHouse performance. You will learn how to design schemas that maximize the benefits of columnar storage, how to choose ORDER BY and PARTITION BY clauses that align with your query patterns, how to use indexing effectively, and how to avoid anti-patterns that degrade performance by orders of magnitude.

The third section covers the storage layer: compression algorithms, storage engines beyond MergeTree, disks and volumes, tiered storage configurations, and object storage integration. At petabyte scale, storage decisions directly determine both performance and cost. The wrong compression choice can waste millions of dollars in storage. The wrong storage policy can make cold data queries unusably slow.

The fourth section covers distribution and replication. How to design shard topologies for your workload, how to configure ReplicatedMergeTree for high availability, how Distributed tables route queries across the cluster, and how to manage the ZooKeeper or ClickHouse Keeper coordination layer that keeps everything in sync. This is where single-node performance becomes multi-node reliability.

The fifth section covers ingestion: how to batch writes efficiently, how to integrate with Kafka for streaming ingestion, how to handle high-throughput pipelines without overwhelming your cluster, and how to manage data lifecycle with TTLs and mutations.

The sixth section covers query optimization: how to read EXPLAIN plans, how to diagnose and fix slow queries, how to configure resource limits to prevent runaway queries, how materialized views and projections accelerate reads, and how distributed queries execute across shards.

The seventh section covers operations: hardware selection and capacity planning, cloud versus self-managed deployments, Kubernetes configuration, monitoring and alerting, backup and disaster recovery, security and multi-tenancy, upgrades and migrations, and systematic troubleshooting. These are the day-to-day skills that keep production clusters running.

The final section brings it all together with architectural patterns from real-world deployments, covering how teams organize their clusters for different workload types and the lessons learned from operating at scale.

How to Use This Book

Read this book in order if you are new to ClickHouse. The early chapters build the mental models needed to understand the later ones. If you already know ClickHouse and need to solve a specific problem, jump to the relevant chapter. Each chapter is designed to be readable standalone, with enough context to stand on its own.

Every substantial code example is explained line by line. You will find SQL for creating tables and indexes, XML and YAML for server configuration, shell scripts for automation, Kubernetes manifests for deployments, and monitoring configurations for observability stacks. The examples are production-oriented and use realistic naming and sizing. They are not toy snippets.

Throughout the book, I mark three types of content differently:

- Documented facts from official ClickHouse documentation or source code are presented as-is. These are things that work a certain way because they are implemented that way.
- Engineering recommendations based on production experience and community practice are explicitly labeled as such. These are things that work well in practice but may have alternatives depending on your specific situation.
- Opinions and assessments that reflect my judgment about trade-offs are framed as my own evaluation, with the reasoning shown so you can decide for yourself.

Version Context

ClickHouse is actively developed with new features and breaking changes in each release. The material in this book is based on ClickHouse versions 24.8 through 26.x, which represent the current stable and bleeding-edge releases at the time of writing. Where a feature or behavior is version-specific, I call it out explicitly.

The core architecture has been stable for many years. Columnar storage, MergeTree, vectorized execution, sparse indexing, and distributed table mechanics have not fundamentally changed. The areas that evolve most rapidly are integration features, coordination layers, and data lake support. I note where new features are still maturing and where production readiness is not yet guaranteed.

Prerequisites

This book assumes you are comfortable with:

- SQL syntax and database concepts (tables, indexes, joins, aggregation)
- Linux system administration basics (file systems, process management, networking)
- Basic distributed systems concepts (latency, throughput, partitions, replicas, consistency)
- Command-line usage and scripting

If you have run databases in production, managed Linux servers, or operated data pipelines, you have the background to follow along. If you are new to these areas, you may want to build that foundation first before tackling ClickHouse at scale.

Why ClickHouse Is Different

Before diving in, it is worth understanding what makes ClickHouse fundamentally different from other databases you may know. This shapes how you think about it and prevents you from applying patterns from OLTP systems that will not work here.

ClickHouse is a column-oriented analytical database optimized for scan-heavy read workloads[1]. It is not designed for random access, row-level updates, or high-concurrency OLTP transactions. The performance comes from three core properties:

Columnar storage means each column is stored separately on disk. When a query only needs three columns from a table with fifty, ClickHouse reads only those three columns. Combined with compression, this reduces I/O by an order of magnitude or more compared to row stores that must read every column for every row.

Vectorized query execution means the CPU processes arrays of values instead of individual rows. Operations are performed in batches that fit in CPU cache, leveraging SIMD instructions for parallel processing within each core. This reduces overhead and maximizes CPU utilization for analytical queries.

Immutable, sorted data with background merges means writes are fast appends that create new data parts on disk, and a background process continuously merges these parts into larger, sorted chunks. This eliminates write amplification from B-tree balancing and allows reads to take advantage of sorted data for efficient range scans.

These properties make ClickHouse extraordinarily fast for analytical queries on large datasets. They also mean certain things that are trivial in OLTP databases become expensive or impractical here. Row-level updates require rewriting entire data parts. Complex joins are limited compared to general-purpose query engines. Transactional guarantees are different and weaker. Understanding these trade-offs is the foundation for everything else in this book.

The next chapter examines the architecture and internals in detail, explaining how all these pieces fit together and why they behave the way they do.

Chapter 1: Why ClickHouse at Scale

Columnar Storage and the Analytics Workload

The fundamental reason ClickHouse exists is that traditional databases handle analytical workloads poorly. The problem starts with how data is stored. Row-oriented databases like PostgreSQL and MySQL store all columns for a single row contiguously on disk. This layout is excellent for transactions: when you read or update a user record, you want all fields nearby. It is terrible for analytics.

Consider a query that counts page views by country from a billion-row events table:

```
SELECT country, COUNT(*) AS views
FROM page_events
WHERE event_date >= '2026-01-01'
GROUP BY country
```

A row-oriented database must read every column for every matching row, even though only `country` and `event_date` are used. If the table has fifty columns averaging fifty bytes each, the database reads five thousand bytes of data for each row just to extract a two-byte country code and a four-byte date. The I/O amplification is extreme.

ClickHouse stores columns separately. Each column is a file, or more precisely a set of files organized by data parts. The same query reads only the `country` and `event_date` columns: maybe fifty bytes total per row instead of five thousand. That is a one hundred-fold reduction in I/O before compression is even considered.

This benefit compounds with compression. Columnar data compresses dramatically better than row data because values in a single column tend to have similar types and patterns. A column of timestamps contains only timestamps. A column of country codes contains only country codes. Compression algorithms find repeating patterns and encode them efficiently. Low-cardinality columns like country codes can achieve compression ratios of fifty

to one or more. Even high-cardinality text columns compress at five to ten times their uncompressed size.

The combination of reading fewer columns and compressing better means analytical queries touch orders of magnitude less disk data. At petabyte scale, this difference determines whether a query finishes in seconds or hours.

ClickHouse uses this columnar foundation for everything. The MergeTree engine family stores each column as separate files within each data part. The compression codecs are applied per-column, allowing different compression strategies for different data types. The indexing is optimized for skipping large chunks of columnar data. The query execution engine processes entire columns as vectors.

Understanding columnar storage is not just theoretical background. It informs every schema design decision. The choice of data types affects both uncompressed size and compression ratio. The order of columns in a query affects memory pressure during execution. The choice of compression codecs per column affects write speed, read speed, and storage cost. You cannot optimize ClickHouse without thinking in columns.

ClickHouse in the Data Stack

ClickHouse occupies a specific niche in modern data architecture. It is not meant to replace every database in your stack, and trying to do so is a recipe for operational pain. Understanding where ClickHouse fits helps you use it for what it is good at and leave other jobs to other systems.

The typical placement for ClickHouse is as the primary analytical store for real-time workloads. Data flows from applications and systems through ingestion pipelines into ClickHouse, where it is queried directly by dashboards, APIs, alerting systems, and ad-hoc analysis tools. This architecture provides sub-second query latency on fresh data without the complexity and cost of a traditional data warehouse ETL pipeline.

Compare this to the traditional data warehouse pattern. In that model, raw data lands in object storage, is batch-processed by a transformation engine like Spark, and loaded into a warehouse like Snowflake or BigQuery on an hourly or daily schedule. This works well for historical analysis with latency requirements measured in hours. It does not work for use cases that need answers within seconds of data arriving.

ClickHouse supports both patterns. You can ingest data in near real-time and query it immediately, or you can use it as a faster, more cost-effective alternative to traditional warehouses for batch analysis. Many organizations use ClickHouse for both: real-time dashboards querying the hot data tier while analysts run complex reports across historical data in cold storage.

ClickHouse is not suited for:

- High-concurrency OLTP transactions with strong consistency requirements. Use PostgreSQL, MySQL, or similar.
- Low-latency key-value lookups. Use Redis, DynamoDB, or a dedicated document store.
- Full-text search with complex relevance ranking. Use Elasticsearch or a dedicated search engine.
- Graph queries with deep traversals. Use a graph database.

ClickHouse can technically do some of these things, but you will not be happy with the results. Using ClickHouse as a general-purpose database leads to over-engineering, performance issues, and operational complexity without getting the benefits that make it valuable.

Where ClickHouse excels is as a specialized analytical engine for:

- Real-time log analytics and observability
- Clickstream and event analytics
- Time-series monitoring and alerting
- Fraud detection and anomaly detection
- Real-time business intelligence dashboards
- Telemetry and IoT analytics
- Ad-tech and bidding analytics
- Feature stores for machine learning

In all these cases, the workload pattern is the same: high-volume ingestion of append-only data, scan-heavy queries that aggregate across large datasets, and latency requirements measured in milliseconds to seconds rather than hours to days.

Performance Characteristics: Why It Is So Fast

ClickHouse is fast for specific reasons. The marketing claims are not exaggeration, but understanding what drives the performance matters more than the numbers themselves. Here are the key factors that enable ClickHouse to process billions of rows in seconds:

Columnar storage reduces I/O dramatically, as explained earlier. But the benefit extends beyond just reading fewer bytes. Columnar data layouts enable compression that makes I/O almost irrelevant for analytical queries. A billion rows of typical event data that might occupy fifty gigabytes uncompressed can fit in a few gigabytes compressed and columnar. Reading a few gigabytes sequentially from modern NVMe SSDs takes less than a second.

Vectorized query execution maximizes CPU utilization. Instead of processing rows one at a time with function calls and branching overhead, ClickHouse processes blocks of columns using SIMD instructions. A single CPU instruction operates on multiple values simultaneously. This reduces overhead per row and keeps CPU caches filled with relevant data. The execution engine is built around Block objects that hold column chunks, and operations are vectorized at every stage from filtering to aggregation.

Sparse indexing enables skipping data without reading it[1]. Unlike B-tree indexes in OLTP databases that provide exact lookup, ClickHouse uses sparse primary keys that record values at regular intervals: one entry per eight thousand rows by default[2]. This index is small enough to fit in memory for very large tables and enables the database to skip entire ranges of rows that do not match the query. Combined with partition pruning and skip indexes, ClickHouse can often read less than one percent of the data in a table to answer a query.

Sorted data enables efficient range scans. Data in MergeTree tables is sorted by the primary key columns. When a query filters on those columns, ClickHouse can seek directly to the relevant range and read only contiguous blocks of data. This eliminates random I/O and allows sequential reads that modern storage devices optimize for.

Single-threaded design per query reduces coordination overhead. Each query runs in a single thread with multiple CPU slots for parallelism within that thread. This eliminates lock contention and context switching overhead that multi-threaded designs incur. The ConcurrencyControl mechanism manages

CPU slots across queries to prevent resource exhaustion.

Data skipping indexes reduce work for specific patterns. Beyond the sparse primary key, ClickHouse supports various skip indexes that record additional information about data ranges: min-max values, bloom filters, sets of values, full-text indexes, and vector similarity indexes. These allow queries to skip data based on non-primary-key columns without scanning it first.

The numbers tell the story. In ClickHouse's own benchmarks, queries scan billions of rows per second on commodity hardware. Real-world deployments process similar volumes: Netflix handles five petabytes of logs daily with sub-second query latency. PostHog serves analytics for millions of users with queries across billions of events completing in under two seconds. These are not synthetic benchmarks; these are production systems under real load.

But performance is not free. These optimizations come with trade-offs that affect how you use ClickHouse:

- Inserts are batch-oriented, not row-oriented. Single-row inserts are extremely slow compared to batched inserts.
- Updates and deletes are expensive. They rewrite entire data parts in the background.
- Joins have limitations. Cross-shard joins in distributed queries require data movement.
- Concurrency is limited. ClickHouse handles dozens to hundreds of concurrent queries well, not thousands.
- Transactions are not supported in the ACID sense. Replication provides eventual consistency, not strong consistency.

Understanding these trade-offs is essential. They explain why certain patterns work in ClickHouse and others do not, and they guide the architectural decisions in later chapters.

What ClickHouse Is Not Built For

It is equally important to understand what ClickHouse should not be used for. The database excels at analytical workloads, but applying it to inappropriate use cases leads to operational nightmares and frustrated teams.

ClickHouse is not an OLTP database. It does not provide ACID transactions with row-level locking. It is not designed for high-frequency, low-latency point reads and updates. A workload of thousands of concurrent users each issuing individual INSERT and SELECT statements with one-row results will perform poorly and may overwhelm the system. The batching requirements and write-optimized design are fundamentally incompatible with transactional patterns.

ClickHouse is not a general-purpose join engine. It supports joins, but they are limited compared to databases designed for relational queries. Cross-shard joins in distributed clusters require data movement that can be expensive. Joins between very large tables without good filters can consume massive amounts of memory. Complex queries with many joins are possible but often perform better with pre-aggregated data in materialized views or projections.

ClickHouse is not a search engine. It has text search capabilities via skip indexes and functions, but it does not provide the sophisticated relevance ranking, full-text search optimization, or fuzzy matching of Elasticsearch. Using ClickHouse as your primary search backend means sacrificing search quality and developer experience.

ClickHouse is not a data warehouse replacement in every scenario. It works well for many warehouse workloads, especially those requiring low latency on fresh data. But traditional warehouses often have stronger support for complex transformations, data governance features, and enterprise integrations. ClickHouse requires more operational effort and less hand-holding than managed warehouses.

ClickHouse is not a graph database. Graph traversals that follow relationships through many hops are inefficient in ClickHouse. The columnar layout is optimized for scanning and aggregating, not for navigating connected data.

ClickHouse is not designed for frequent schema changes. While it supports ALTER TABLE operations, frequent schema changes can disrupt merges and performance. Schema evolution should be planned carefully, especially in production clusters with large tables.

Real-World Scale: Production Deployments in the Field

The best evidence for ClickHouse's capabilities comes from real deployments where organizations operate it at scale in production. These case studies

provide concrete reference points for what is possible and what operational patterns work.

Netflix runs ClickHouse for log analytics across its entire streaming infrastructure. The system ingests five petabytes of logs daily, processing over ten million events per second[39]. Queries across this dataset return results in under two seconds[39]. Netflix achieved this scale through several architectural decisions: using ClickHouse for logs rather than Elasticsearch, generating custom lexers for log fingerprinting instead of relying on generic parsers, and implementing a custom native protocol for ingestion that reduces serialization overhead. The cluster spans multiple regions and uses distributed tables to provide unified queries across all data.

Uber uses ClickHouse for analytics across its ride-hailing and delivery platforms. The original logging system was based on Hadoop and Elasticsearch, which proved too slow and expensive at scale. Uber migrated to ClickHouse and achieved significant improvements in query performance and cost efficiency. A key architectural decision was separating query and data nodes: data nodes hold the actual MergeTree parts, while a smaller set of query nodes handles distributed query fan-out. This separation allows independent scaling of storage and compute and makes cluster topology changes easier.

PostHog, an open-source product analytics platform, runs ClickHouse as its core data store. The platform serves millions of users analyzing billions of events across their products. PostHog's architecture uses a sharded ClickHouse setup with dedicated clusters for different workloads: a primary cluster for event data, a separate cluster for session recordings, and additional clusters for specific products. This workload isolation prevents noisy neighbor problems and allows tuning each cluster for its specific access patterns. PostHog maintains an extensive engineering handbook documenting their ClickHouse practices, which has become a valuable resource for the community.

Lyft replaced Druid with ClickHouse for analytics, citing simpler operations and better cost efficiency. The migration was driven by operational complexity: Druid required managing many components and had a steep learning curve, while ClickHouse provided similar or better performance with simpler infrastructure. The key insight was that ClickHouse's MergeTree engine handles time-series analytics as well as specialized time-series databases, eliminating the need for a separate system.

Zomato uses ClickHouse for a petabyte-scale logging platform that replaced

a more complex and expensive architecture. The migration was motivated by cost: ClickHouse provided the required analytics capabilities at a fraction of the cost of their previous setup. The platform ingests logs from all services and applications, providing real-time visibility into system health and performance.

The common thread across these deployments is that ClickHouse is used for what it is designed to do: high-volume ingestion of append-only data with scan-heavy analytical queries. Organizations that try to use it for OLTP, search, or other workloads struggle. Those that align their architecture with ClickHouse's strengths achieve excellent results.

Another pattern is workload isolation. Large deployments typically use multiple clusters rather than one massive cluster trying to serve everything. Separate clusters for hot and cold data, for different teams, for different products, or for different query patterns all reduce operational complexity and prevent interference between competing workloads.

These real-world examples demonstrate that ClickHouse can handle petabyte-scale workloads in production. They also show that successful deployments require careful architectural decisions around cluster topology, data modeling, ingestion patterns, and workload management. The next chapters examine these topics in detail.

The following chapter dives into ClickHouse architecture and internals, explaining how the system works under the hood and why these design choices enable the performance that makes ClickHouse valuable at scale.

Chapter 2: Architecture and Internals

Request Flow from Client to Disk

Understanding how a request moves through ClickHouse is essential for understanding how to configure and troubleshoot the system. The flow differs depending on whether you are using a single node or a distributed cluster, but the core path on each node is the same.

A client connects to ClickHouse via one of two primary interfaces: HTTP or the native TCP protocol. The HTTP interface listens on port 8123 by default and accepts SQL queries as form data or request body, returns results as text or various formats, and supports data ingestion via POST requests. The native protocol on port 9000 is binary, supports compression, and is used by most client libraries and the clickhouse-client command-line tool. For production workloads, the native protocol is recommended due to better performance and lower overhead.

When a query arrives, ClickHouse processes it through several stages. First, the connection is authenticated against the configured user accounts. This involves checking credentials, host restrictions, and whether the user has permissions for the requested operation. Modern ClickHouse configurations use SQL-driven access control stored in the `access` directory, though legacy XML-based configuration in users.xml still works.

The query string is parsed by a hand-written recursive descent parser into an abstract syntax tree. This AST represents the logical structure of the query without yet considering optimization or execution. The parser enforces syntax rules and identifies semantic issues like undefined tables or type mismatches early.

The AST is then processed by an interpreter, such as InterpreterSelectQueryAnalyzer introduced in version 26.9, which converts the logical query into a physical execution plan. This step performs several optimizations: eliminating unused columns, pushing filters down to reduce data scanned, choosing join algorithms, selecting indexes to use, and determining whether

partitions can be pruned. The output is a query plan that specifies the sequence of operations needed to produce the result.

From the query plan, ClickHouse builds a query pipeline using the processor framework. Each operation in the plan becomes one or more processors that transform blocks of data. A processor reads input blocks, applies its operation, and produces output blocks. Processors are chained together so that output from one becomes input to the next. This pipeline architecture enables streaming execution: data flows through the pipeline without needing to materialize intermediate results entirely in memory.

For a SELECT query on a MergeTree table, the pipeline starts with a reading processor that loads data from disk. The processor uses the partition and index information to identify which data parts and granules need to be read. It reads the relevant column files from those granules into memory as Block objects, which are then passed through filtering, projection, and aggregation processors in the pipeline.

For an INSERT query, the pipeline is simpler. The input data is validated against the table schema, converted to internal column representations, and written as a new data part to disk. For MergeTree tables, the data is sorted according to the ORDER BY clause before being written. The new part is then registered in the parts metadata, making it visible to subsequent queries.

In a distributed cluster, the flow includes additional steps. When a query is sent to a Distributed table, the coordinating node rewrites the query for each shard based on the sharding configuration and forwards it to the appropriate nodes. Each shard executes the query locally using the path described above and returns its partial results. The coordinating node merges the results from all shards and returns the final result to the client.

Understanding this flow matters for several reasons. If authentication is slow, check user configuration and access control settings. If parsing takes too long, check for complex queries that stress the optimizer. If data reading is slow, check partitions, indexes, and storage performance. If pipeline execution is slow, check memory configuration and parallelism settings. If distributed queries are slow, check shard balance and network latency. The request flow provides a framework for isolating performance issues.

The MergeTree Storage Engine Family

The MergeTree family of storage engines is the heart of ClickHouse. Nearly every production table uses MergeTree or one of its variants. Understanding how MergeTree works explains most of ClickHouse's performance characteristics and limitations.

MergeTree tables store data in immutable parts. Each INSERT operation creates one or more new parts on disk. A part contains a subset of the table's data, sorted according to the ORDER BY clause. Parts are never modified in place. When data needs to be changed, ClickHouse creates new parts with the updated data and discards the old ones. This immutable design eliminates the write amplification and fragmentation problems of in-place update databases.

Parts are organized into levels based on their size. Level 0 contains the smallest parts: typically the raw parts created by INSERT operations. Level 1 contains parts formed by merging two or more level-0 parts. Level 2 contains parts formed by merging level-1 parts, and so on. This hierarchy is maintained by a background merge process that continuously combines smaller parts into larger ones. Larger parts mean fewer files to open during queries, which improves read performance.

Each part is stored in a directory containing column files, index files, and metadata. The directory structure follows a specific naming convention that encodes the partition key, the range of primary key values, and the part level. For example, a part directory might be named `20260101_20260131_12345_12349_5`, indicating a part covering January 1 through 31, with primary key values from 12345 to 12349, at level 5.

Within each part, data is further divided into granules. A granule is a group of rows: eight thousand by default, configurable via the index_granularity table setting. The granule is the smallest unit of data that ClickHouse can skip or read based on index lookups. When a query filters on the primary key, ClickHouse checks the sparse primary key index to determine which granules might contain matching rows and skips the rest.

The MergeTree family includes several variants that handle different data patterns:

- Plain MergeTree: basic sorted, immutable storage with background merges

- ReplicatedMergeTree: adds replication via ZooKeeper or ClickHouse Keeper
- ReplacingMergeTree: automatically removes duplicate rows based on a version column during merges
- CollapsingMergeTree: supports logical deletes and updates using a sign column
- SummingMergeTree: automatically sums numeric columns for rows with the same key during merges
- AggregatingMergeTree: designed for use with materialized views and aggregate functions
- VersionedCollapsingMergeTree: an enhanced version of CollapsingMergeTree with better handling of out-of-order data

Each variant shares the same core part-based storage and merge behavior but adds specific logic during merges to handle duplicates, logical updates, or aggregations. Choosing the right variant depends on your data patterns and whether you need to handle updates or deduplication.

MergeTree requires at least an ORDER BY clause in the CREATE TABLE statement. This clause specifies the sorting key: the columns by which data is sorted within each part. If no PRIMARY KEY is specified, the sorting key also serves as the primary key. The primary key can be a subset of the sorting key columns but cannot include columns not in the sorting key. This design ensures that the physical data layout matches the logical index structure.

Other optional clauses include PARTITION BY for organizing data into logical partitions, SAMPLE BY for sampling queries, and TTL for automatic data lifecycle management. Each of these affects how data is stored, merged, and queried.

The merge process is central to MergeTree behavior. Merges run in the background continuously, combining smaller parts into larger ones. Merges are CPU and I/O intensive because they must read all data from the input parts, sort it if necessary, apply any variant-specific logic like deduplication, and write new output parts. Merges compete with queries for resources, which is why merge configuration matters for production clusters.

The number of parts in a table directly affects query performance. Too many parts means the query must open many files, increasing latency. Too few large parts means merges can take a long time and consume excessive resources.

The merge scheduler tries to maintain a balance by prioritizing merges that create larger parts while respecting resource limits.

Query Execution Engine and Pipelines

ClickHouse's query execution engine is built around vectorized processing and streaming pipelines. This design is fundamentally different from row-at-a-time execution in OLTP databases and is what enables ClickHouse to process billions of rows in seconds.

At the core of execution is the Block data structure. A Block represents a chunk of columnar data in memory: each column as an IColumn instance, each with its data type described by an IDataType. Blocks are the units that flow through the query pipeline. A typical block might contain a few thousand rows of data for each column referenced by the query.

The processor framework executes queries as pipelines of processors. Each processor type performs a specific operation: reading data from disk, filtering rows, projecting columns, sorting, aggregating, joining, and so on. Processors read input blocks, apply their operation in vectorized fashion, and produce output blocks. The pipeline is constructed from the query plan: a ReadFromMergeTree processor at the beginning feeds into Filter processors, which feed into Aggregator processors, and so on.

Vectorized execution means operations are applied to entire columns or blocks at once using SIMD instructions instead of processing rows individually. A filter operation reads a boolean array and selects matching rows from all columns simultaneously. An aggregation operation processes arrays of values in parallel, accumulating results in CPU registers. This approach reduces function call overhead, improves cache utilization, and enables the CPU to process multiple values per instruction.

The pipeline architecture enables streaming execution. Data flows through processors as it is read from disk without materializing all intermediate results in memory. This keeps memory usage bounded and allows queries to start producing results quickly. For large result sets, rows are sent to the client as they are computed rather than waiting for the entire result.

Parallelism is achieved within the pipeline through concurrent processing. A reading processor can use multiple threads to read different granules or parts simultaneously. An aggregation processor can use multiple threads

to aggregate different subsets of data in parallel before combining results. The degree of parallelism is controlled by the max_threads setting and the ConcurrencyControl mechanism.

The ConcurrencyControl mechanism manages CPU slots across all queries in the system. Each query is allocated a certain number of CPU slots based on its priority and the system load. Processors acquire slots before performing CPU-intensive work and release them when done. This prevents queries from oversubscribing CPU resources and ensures fair scheduling under load. The total number of CPU slots is typically set to a multiple of the actual CPU cores to allow for parallelism without overcommitting.

Execution plans are optimized before the pipeline is built. The optimizer applies several transformations:

- Column pruning: removing columns that are not needed in the final result
- Partition pruning: eliminating partitions that cannot contain matching rows based on filters
- Index usage: determining which primary key ranges and skip indexes to use
- Predicate pushdown: pushing filter conditions as close to the data source as possible
- Join optimization: choosing appropriate join algorithms and order
- Materialization decisions: determining when to spill to disk versus keeping in memory

These optimizations are critical for performance. A query that scans all data in a table can take minutes or hours on a petabyte-scale dataset. Proper optimization can reduce the data scanned to a tiny fraction, completing the same query in seconds. The EXPLAIN statement allows you to inspect the optimized plan and verify that optimizations are working as expected.

Memory Management and Allocations

Memory management is crucial in ClickHouse because analytical queries can require large amounts of memory for operations like sorting and aggregation. A single poorly designed query can consume all available memory and crash the server. ClickHouse provides multiple levels of memory control to prevent this.

At the query level, the max_memory_usage setting limits how much memory a single query can consume. The default is typically one gigabyte, which is appropriate for most queries but may need to be increased for large aggregations. When a query exceeds this limit, ClickHouse returns a MEMORY_LIMIT_EXCEEDED error. You can set this per-query using the SETTINGS clause or configure it for specific users or roles.

At the server level, the max_server_memory_usage setting limits total memory across all queries. This prevents a cluster of queries from consuming all available memory and starving the operating system. The max_server_memory_usage_to_ram_ratio setting expresses this as a fraction of available RAM.

For operations that might exceed per-query limits, ClickHouse supports external aggregation and sorting. When max_bytes_before_external_group_by is set, aggregation operations spill intermediate results to disk once they exceed the threshold. Similarly, max_bytes_before_external_sort enables disk-based sorting. These settings allow queries to complete successfully using more data than fits in memory at the cost of slower execution.

The ClickHouse memory allocator manages allocations efficiently for the columnar data patterns. Columnar data means large contiguous allocations for each column, which the allocator can handle efficiently. The allocator tracks memory usage per query and per component, enabling accurate enforcement of limits and detailed diagnostics.

System tables expose memory usage for monitoring and troubleshooting. system.processes shows memory usage for each running query. system.asynchronous_metrics shows total memory usage across merges, dictionaries, caches, and other components. The debugging query examples in the documentation query these tables to identify memory consumers.

Memory caching plays a significant role in performance. ClickHouse maintains a mark cache that stores file positions for granules, a primary key cache for index lookups, and a filesystem cache that stores recently accessed data blocks. These caches reduce disk I/O for frequently accessed data but consume memory that could be used for queries. Cache sizes are configurable and should be tuned based on workload patterns.

At petabyte scale, memory management becomes a critical operational concern. Under-provisioned memory leads to slow queries that spill to disk or fail with memory errors. Over-provisioned memory wastes money. The sizing

guidelines recommend memory-to-storage ratios based on workload: one to one for small datasets where everything fits in cache, one to thirty to fifty for frequently accessed data, and one to one hundred or more for long-retention data that is rarely queried.

Single-Threaded Design Philosophy

ClickHouse's single-threaded design per query is one of its most distinctive and consequential architectural choices. Most database systems use multi-threaded execution where each query uses multiple threads for different operations. ClickHouse instead runs each query in a single thread with CPU slot-based parallelism. This design has significant implications for performance, reliability, and concurrency.

In ClickHouse, each query is assigned to a server thread from a thread pool. That thread orchestrates the entire query execution: parsing, planning, building the pipeline, and coordinating data flow. The thread does not use additional operating system threads for parallelism within the query. Instead, it uses the CPU slot mechanism to coordinate parallel work across multiple processors in the pipeline.

The ConcurrencyControl component tracks CPU slots across the system. When a processor needs to do CPU-intensive work, it requests CPU slots. The request is granted if slots are available, or the processor blocks and waits. This allows multiple queries to share CPU resources without actually running multiple OS threads per query.

The benefits of this design are significant. Thread management overhead is eliminated. There is no lock contention between threads in the same query. Context switching is reduced. The single-threaded model makes it easier to reason about query execution and debug issues. Memory usage is more predictable because there are fewer threads consuming stack and thread-local memory.

The design also affects concurrency. ClickHouse can handle dozens to hundreds of concurrent queries effectively, depending on the hardware and workload. This is sufficient for most analytical workloads where queries are relatively slow and concurrency is limited. It is not sufficient for OLTP workloads that require thousands of concurrent transactions per second.

The CPU slot mechanism provides fairness and prioritization. Queries can be assigned different priorities: normal queries get standard priority, while important queries or administrative operations can get higher priority. When the system is under load, higher-priority queries get CPU slots first, ensuring they complete in a timely manner.

This design philosophy extends to other parts of ClickHouse. Insert operations are similarly single-threaded per query, processing blocks sequentially. Merge operations run in dedicated background threads but are also single-threaded per merge. This consistency simplifies the codebase and reduces complexity.

For operators, the single-threaded design means that query performance scales primarily with CPU core count. More cores mean more CPU slots available for parallelism within queries and more threads available for concurrent queries. The hardware sizing recommendations reflect this: choose instance types with more cores for workloads that need faster query performance or higher concurrency.

Understanding this design helps explain why ClickHouse behaves the way it does under load. It explains why concurrency is limited compared to OLTP databases, why CPU is the primary bottleneck for most queries, and why adding more cores is the most effective way to scale query performance vertically.

The next chapter dives deeper into MergeTree, examining the data parts structure, the merge process, and the variants of the MergeTree engine in the detail that production engineers need to understand to configure and tune their tables effectively.

Chapter 3: MergeTree Deep Dive

Data Parts and Part Levels

The concept of data parts is fundamental to MergeTree. Every piece of data in a MergeTree table exists within a part. Understanding how parts are organized, named, and managed is essential for troubleshooting, monitoring, and optimizing ClickHouse tables.

Each INSERT into a MergeTree table creates one or more new parts. If you insert a million rows in a single INSERT statement, ClickHouse creates a part containing those million rows. If you insert that same million rows in ten INSERT statements of one hundred thousand rows each, you get ten separate parts. This behavior explains why batch size matters so much for performance: fewer parts means less overhead for queries and merges.

Parts are stored in a specific directory structure under the table's data directory:

```
/var/lib/clickhouse/data/<database>/<table>/
├── 20260101_20260131_12345_12349_0/
├── 20260201_20260228_23456_23460_0/
├── 20260101_20260131_12345_23460_1/
└── detaching/
```

Each part directory name encodes important information. The format is:

```
<partition_id>_<min_primary_key>_<max_primary_key>_<partition>_<level>
```

For example, `20260101_20260131_12345_12349_0` indicates:

- Partition ID: a hash of the partition key value (20260101 for January 2026)
- Min primary key: 12345 (the smallest primary key value in the part)
- Max primary key: 12349 (the largest primary key value in the part)
- Partition number: 0 (an internal identifier)

- Level: 0 (the part level in the merge hierarchy)

Part levels reflect the merge history. Level 0 parts are the original parts created by INSERT operations. When ClickHouse merges two or more level-0 parts, it creates a level-1 part. Merging level-1 parts creates level-2 parts, and so on. Higher-level parts are larger and fewer in number, which improves query performance.

Within each part directory, you find the actual data files:

```
20260101_20260131_12345_12349_0/
├── columns/
│   ├── event_date/
│   │   ├── data.bin
│   │   └── index.bin
│   ├── user_id/
│   │   ├── data.bin
│   │   └── index.bin
│   └── ...
├── primary.idx
├── checksums.txt
├── count.txt
└── minmax_*.idx
```

Each column has its own directory containing compressed data files and index files. The `primary.idx` file stores the sparse primary key index: one entry per granule (eight thousand rows by default). The minmax files store the minimum and maximum values for each column in each granule, enabling data skipping. The checksums file stores checksums for integrity verification, especially important for replicated tables.

MergeTree supports two part formats: wide and compact. Wide parts store each column in separate files, which is efficient for queries that access only some columns. Compact parts store columns together in fewer files, reducing the number of open file descriptors and improving write performance for small parts. The choice is controlled by `min_bytes_for_wide_part` and `min_rows_for_wide_part` settings. Parts below these thresholds use compact format. For most production tables, you want wide parts, so set these thresholds low enough that parts are almost always wide.

The number of parts in a table is a critical metric for operational health. You can check it with:

```
SELECT
    table,
    count() AS parts,
    sum(rows) AS rows,
    formatReadableSize(sum(data_compressed_bytes)) AS size
FROM system.parts
WHERE active
GROUP BY table
ORDER BY parts DESC
LIMIT 20;
```

A table with too many parts indicates a problem. Common causes include high-frequency small inserts, too-fine partitioning that prevents parts from merging, or merge settings that are too conservative. When a table has too many parts, queries suffer from increased latency because they must open many files and process many small ranges. ClickHouse even enforces a maximum parts per partition limit, defaulting to about one hundred parts, and returns an error when exceeded.

The Merge Process and Background Merges

Merges are the lifeblood of MergeTree. They continuously combine smaller parts into larger ones, maintaining table health and query performance. Understanding how merges work is essential for configuring them correctly and troubleshooting merge-related issues.

Merges run in the background in dedicated threads from a merge pool. The default pool size is based on the number of CPU cores. When a merge thread becomes available, it selects parts to merge based on a scoring algorithm that prioritizes certain types of merges over others. The selection criteria balance multiple goals: reducing the total number of parts, creating larger parts that improve query performance, and respecting resource limits to avoid starving queries.

The merge algorithm is straightforward but resource-intensive. It reads all data from the input parts, sorts it according to the ORDER BY clause, and writes a new output part. For plain MergeTree, this is a standard multi-way merge of already-sorted inputs. For variants like ReplacingMergeTree, additional logic runs during the merge to handle deduplication or aggregation.

Merges have several characteristics that affect production operations:

They are CPU-intensive. Merging large parts requires reading, decompressing, sorting, re-compressing, and writing data. A merge that processes a hundred gigabytes of compressed data might take several minutes and consume significant CPU during that time.

They are I/O-intensive. Merges read all columns from all input parts and write all columns to the output part. This generates substantial disk I/O, which can compete with query I/O for bandwidth.

They create temporary disk usage. During a merge, both input and output parts exist on disk simultaneously. A merge that creates a one hundred gigabyte output part from fifty gigabyte inputs temporarily requires two hundred gigabytes of disk space. When disk space is constrained, merges can fail or be blocked.

They respect resource limits. ClickHouse monitors system load and throttles merges when queries are consuming resources. The merge pool size, maximum merge size, and load thresholds are all configurable to balance merge progress against query performance.

Merge configuration settings control how aggressively merges run:

```
<merge_tree>
    <!-- Maximum number of parts that can be selected for one merge -->
    <max_parts_to_merge_at_once>10</max_parts_to_merge_at_once>

    <!-- Maximum total size of parts that can be merged when the merge pool is
    ↪  at capacity -->
    <max_bytes_to_merge_at_max_space_in_pool>15000000000
    ↪  </max_bytes_to_merge_at_max_space_in_pool>

    <!-- Maximum total size of parts that can be merged when the merge pool is
    ↪  nearly empty -->
    <max_bytes_to_merge_at_min_space_in_pool>1048576
    ↪  </max_bytes_to_merge_at_min_space_in_pool>

    <!-- Interval in seconds for removing old unneeded parts from the data
    ↪  directory -->
    <merge_tree_clear_old_parts_interval_seconds>3
    ↪  </merge_tree_clear_old_parts_interval_seconds>
</merge_tree>
```

The default max_bytes_to_merge_at_max_space_in_pool of about one hundred fifty gigabytes is reasonable for most deployments. Larger values allow more aggressive merging but risk consuming too many resources. Smaller

values reduce resource impact but allow parts to accumulate. The setting should be tuned based on available CPU, I/O bandwidth, and the tolerance for part count.

Merges are monitored through system tables. system.merges shows currently running merges:

```
SELECT
    database,
    table,
    elapsed,
    formatReadableSize(bytes_read_uncompressed) AS read,
    formatReadableSize(bytes_written_uncompressed) AS written,
    result_part_name
FROM system.merges
ORDER BY elapsed DESC;
```

system.part_mutations shows pending mutations that need to be applied during merges. system.metrics exposes merge-related metrics including merge queue length and merge operations per second.

At petabyte scale, merge management becomes critical. A cluster with many large tables constantly performing merges can saturate I/O bandwidth and degrade query performance. Strategies for managing merges at scale include:

- Using storage policies to move older data to slower storage where merge frequency is lower
- Tuning merge settings based on workload patterns: more aggressive during off-peak hours, less aggressive during peak query times
- Monitoring merge queue length and adjusting settings when it grows too large
- Partitioning data appropriately so that merges within each partition are manageable

Parts Metadata and the Parts Database

ClickHouse maintains metadata about every part in every table. This metadata is crucial for query planning, merge scheduling, replication, and recovery.

Understanding where this metadata lives and how it is managed helps with troubleshooting and operational procedures.

The parts metadata is stored in system.parts and related system tables. This is not a separate database but a virtual representation of the actual state maintained by the MergeTree engine. When you query system.parts, ClickHouse reads the part directories and metadata files to construct the result.

Key columns in system.parts include:

- name: the part name encoding partition, key range, and level
- partition: the partition identifier
- partition_id: the hash of the partition key
- rows: number of rows in the part
- bytes_on_disk: uncompressed size
- data_compressed_bytes: compressed size on disk
- marks: number of granules
- level: merge level
- active: whether the part is currently visible to queries
- reference_count: number of references (for replication and mutations)

This information is essential for monitoring table health. Queries that check for too many parts, uneven partition sizes, or inactive parts all rely on system.parts.

For ReplicatedMergeTree tables, additional metadata is stored in ZooKeeper or ClickHouse Keeper. This includes:

- The list of parts each replica has
- Log entries for inserts and mutations
- Checksums for data integrity verification
- Replica state information

This ZooKeeper metadata is the source of truth for replication. When a replica starts up or falls behind, it consults ZooKeeper to determine what parts it should have and downloads missing parts from other replicas. If ZooKeeper metadata becomes inconsistent with the actual parts on disk, the replica can enter read-only mode or require manual recovery.

The parts database also tracks mutations. When you run ALTER TABLE DELETE or UPDATE, ClickHouse creates a mutation entry in system.mutations. The mutation specifies the table, partition, and condition for rows to be modified. Merges that process parts matching the mutation condition apply the mutation, creating new parts with the modified data. The mutation is marked as complete when all affected parts have been rewritten.

Monitoring mutations is important for operational health:

```
SELECT
    database,
    table,
    mutation_id,
    command,
    create_time,
    latest_fail_time,
    is_done
FROM system.mutations
WHERE NOT is_done
ORDER BY create_time;
```

Pending mutations indicate background work that has not yet completed. If mutations pile up, it can indicate a problem with merge capacity or that mutations are affecting too many parts.

Out-of-Order Inserts and Data Reordering

In production environments, data often arrives out of order. Events may be timestamped in the past due to processing delays, clock skew, or retries. Log entries from different systems may not arrive in chronological sequence. ClickHouse handles out-of-order inserts through its merge-based design, but understanding how this works helps you choose the right MergeTree variant and tune it correctly.

When an INSERT adds data with primary key values that fall in the middle of an existing part's range, ClickHouse does not modify the existing part. Instead, it creates a new part containing the new rows. At this point, there are overlapping parts with interleaved data. Queries work correctly because ClickHouse reads from all active parts and returns the union of matching rows. The data is logically sorted across parts but physically interleaved.

Over time, merges combine the overlapping parts into larger parts where all rows are physically sorted. During the merge, ClickHouse reads all rows from all input parts, sorts them by the ORDER BY columns, and writes a new part with the correct order. The old parts are then removed.

This approach works well for most workloads. However, it has implications for certain use cases:

If you need strictly ordered data immediately after insert, MergeTree is not the right choice. The data is sorted only after merges complete.

If you insert data out of order frequently, you create many small parts that must be merged later, increasing merge load and the risk of hitting the maximum parts limit.

If you use a MergeTree variant with deduplication, out-of-order inserts can interact with deduplication logic in complex ways.

The ReplacingMergeTree variant addresses some of these concerns. When configured with a version column, ReplacingMergeTree keeps only the row with the highest version value for each key during merges. This allows you to insert updated data with higher version values out of order, and merges will automatically keep the latest version.

However, ReplacingMergeTree does not guarantee that only the latest version is visible. Before merges complete, all versions exist in separate parts and are all visible to queries. To get only the latest version, you must use FINAL:

```
1  SELECT * FROM events FINAL WHERE user_id = 123
```

FINAL forces ClickHouse to read all parts and deduplicate rows on the fly. This is slow for large tables because it prevents any data skipping. The recommended pattern is to use ReplacingMergeTree without FINAL for most queries and accept that there may be temporary duplicates, relying on background merges to clean up.

The VersionedCollapsingMergeTree variant provides better handling of out-of-order data with updates. It uses both a sign column and a version column to track updates, enabling correct deduplication even when updates arrive out of order. This is more complex but provides stronger correctness guarantees than ReplacingMergeTree.

For production systems, the best approach to handling out-of-order data depends on the specific requirements:

- If data arrives mostly in order with occasional late events, plain MergeTree or ReplacingMergeTree works well.
- If data arrives significantly out of order and correctness is critical, VersionedCollapsingMergeTree is appropriate.
- If you cannot tolerate temporary duplicates, consider using a staging table where data is inserted and then periodically loaded into the main table in order.

MergeTree Variants and Their Trade-Offs

The MergeTree family includes several variants designed for specific data patterns. Choosing the right variant affects performance, correctness, and operational complexity. Each variant shares the core MergeTree storage and merge behavior but adds specific logic during merges.

Plain MergeTree is the base engine. It stores sorted data, performs background merges, and provides the core features: primary key indexing, partitioning, TTL, and projections. Use it when you need straightforward append-only storage with no special handling for duplicates or updates.

ReplacingMergeTree removes duplicate rows based on a key during merges. When configured with `ORDER BY (key_column)` and `SETTINGS deduplication_window = 100`, it keeps only the last row for each key value seen within the deduplication window of one hundred inserts. For handling updates, use the version column form:

```
CREATE TABLE events
(
    event_id UInt64,
    user_id UInt32,
    event_time DateTime,
    version UInt64,
    payload String
)
ENGINE = ReplacingMergeTree(version)
ORDER BY (user_id, event_time)
PARTITION BY toYYYYMM(event_time);
```

This keeps the row with the highest version for each (user_id, event_time) combination during merges. Limitations: duplicates are visible until merges complete, requiring FINAL for exact results, which is slow.

CollapsingMergeTree supports logical deletes and updates using a sign column. Each row has a sign: positive for active rows, negative for deleted rows. During merges, pairs of rows with the same key and opposite signs cancel out. This allows you to implement updates by inserting a negative row for the old value and a positive row for the new value:

```
CREATE TABLE events
(
    user_id UInt32,
    event_time DateTime,
    sign Int8,
    payload String
)
ENGINE = CollapsingMergeTree(sign)
ORDER BY (user_id, event_time);
```

CollapsingMergeTree is efficient for workloads with many updates but has complexity: you must ensure that for every negative row there is a corresponding positive row, otherwise rows can disappear unexpectedly. Out-of-order updates can also cause issues.

SummingMergeTree automatically sums numeric columns for rows with the same key during merges. This is ideal for pre-aggregated data where you insert summary rows and want ClickHouse to combine them automatically:

```
CREATE TABLE metrics
(
    metric_name LowCardinality(String),
    timestamp DateTime,
    host String,
    value_sum Float64,
    value_count UInt64
)
ENGINE = SummingMergeTree((value_sum, value_count))
ORDER BY (metric_name, host, timestamp);
```

This is commonly used with materialized views that aggregate raw data into summaries.

AggregatingMergeTree is designed for use with aggregate functions. It stores pre-aggregated data using state objects from aggregate functions. Materialized views with AggregatingMergeTree maintain incremental aggregations:

```
CREATE TABLE user_events_agg
(
    user_id UInt32,
    event_date Date,
    event_count AggregateFunction(count),
    page_views AggregateFunction(sum, UInt32)
)
ENGINE = AggregatingMergeTree()
ORDER BY (user_id, event_date);

CREATE MATERIALIZED VIEW user_events_mv
TO user_events_agg
AS SELECT
    user_id,
    toDate(event_time) AS event_date,
    countState() AS event_count,
    sumState(page_views) AS page_views
FROM user_events
GROUP BY user_id, toDate(event_time);
```

VersionedCollapsingMergeTree is an enhanced version of CollapsingMergeTree that uses version numbers to handle out-of-order updates correctly. It is more complex but provides better correctness guarantees for update-heavy workloads.

Choosing among these variants depends on your data patterns and requirements. For simple append-only data, use plain MergeTree. For handling deduplication or updates, use ReplacingMergeTree or CollapsingMergeTree with understanding of their limitations. For pre-aggregation, use SummingMergeTree or AggregatingMergeTree. The next chapter examines data modeling in detail, including how these choices interact with schema design for optimal performance.

Chapter 4: Data Modeling for ClickHouse

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The Importance of the ORDER BY Clause

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