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Delta Lake Performance Behind the Scenes: From Partitioning to Liquid Clustering

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About me

- Big Data Engineer with extensive experience in Python
- Enthusiastic about math and machine learning
- Big fan of Remembrance of Earth's Past trilogy by Liu Cixin

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Senior Big Data Software Engineer

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Agenda

1. Intro
2. Compaction
3. Partitioning
4. VACUUM
5. Statistics and Data Skipping
6. Z-Ordering
7. Bloom Filter Index
8. Liquid Clustering
9. Summary
10. Q&A

Intro

Introduction

Why Delta Lake Optimization Matters

Key Problems:

- Small files problem: streaming writes, and DML operations generate thousands of tiny files → high metadata overhead, slow object-store listings, increased I/O costs, and poor compression
- Over-partitioning: high-cardinality partition keys (e.g., user_id) create thousands of directories with micro-files → metadata explosion and degraded read performance
- Updates and deletes leave behind outdated files → table size grows and performance declines
- Inefficient data scanning: without proper data layout, queries scan terabytes instead of gigabytes

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Compaction

Reducing Small Files to Speed Up Queries

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Compaction

The Small Files Problem

Root cause:

- **Streaming Ingestion**: writing micro-batches every few seconds/minutes
- **DML Operations**: frequent MERGE, UPDATE, or DELETE actions produce new files
- **Over-partitioning**: splitting data into too many granular folders

Compaction

The Small Files Problem

Performance impact:

- Growth of metadata in the transaction log
- **Metadata overhead**: the driver spends more time listing files in object storage (S3/ADLS) than processing data
- **High I/O latency**: opening/closing thousands of tiny files is inefficient
- **Poor compression**: parquet creates massive overhead (headers/footers) when files are too small

Compaction

OPTIMIZE & Auto Optimize

The **OPTIMIZE** command:

- Triggers **bin-packing**: reads small files and coalesces them into larger files (target size: **1 GB** by default)
- **Idempotent**: running it twice on the same data does nothing
- **ACID**: does not block concurrent readers or writers

Auto Optimize (Automated approach):

- **Optimized writes**: shuffles data **before** writing to reduce file count (increases write latency, improves read)
- **Auto compact**: triggers a "mini-optimize" **after** a write transaction commits

Compaction

ss — vim compaction.sql — vim — vim compaction.sql — 80×24

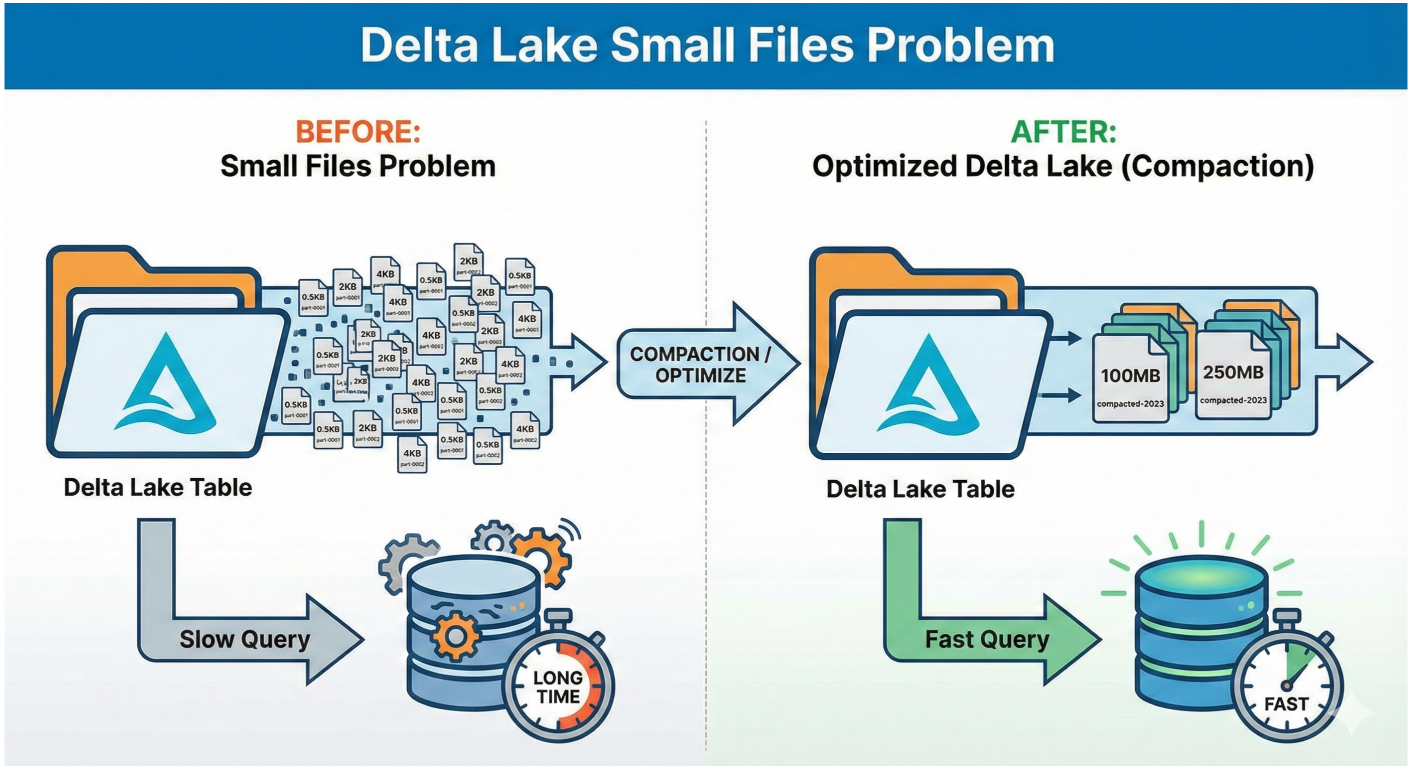
```sql
-- Standard bin-packing
OPTIMIZE events_table;

-- Incremental compaction (Save resources)
OPTIMIZE events_table WHERE date ≥ current_date() - 1;
```

```
"compaction.sql" 5L, 147B
```

ss — vim compaction.py — vim — vim compaction.py — 80×24

```python
spark.databricks.delta.optimizeWrite.enabled = true
spark.databricks.delta.autoCompact.enabled = true
```

Compaction


Delta Lake Small Files Problem
BEFORE:
Small Files Problem
AFTER:
Optimized Delta Lake (Compaction)
COMPACTION / OPTIMIZE
100MB
250MB
Delta Lake Table
Delta Lake Table
Slow Query
LONG TIME
Fast Query
FAST

Compaction

Best Practices

- **Streaming**: enable **Auto Compact** + run OPTIMIZE periodically (e.g., daily/weekly) for cleanup
- **Batch ETL**: run OPTIMIZE at the end of the daily job
- **Strategy**: use **predicates** (WHERE) to avoid compacting the entire table every time

Partitioning

Splitting Data by Keys for Faster Queries

Partitioning

Physical Data Layout

The concept:

- Splitting data into sub-directories based on high-level keys (e.g., Date, Region, Department)
- Structure: s3://bucket/table/date=2024-01-01/region=US/...

The benefit — partition pruning (aka data skipping):

- When a query includes a partition key in the WHERE clause, the engine completely ignores irrelevant directories
- Reduces scanned data from **terabytes** to **gigabytes**

The use case:

- Best for heavy filtering on specific columns (e.g., "Give me data for **Yesterday**").

Partitioning

partitioning.sql

```sql
-- Create a table partitioned by date
CREATE TABLE sales (
  id INT,
  amount DOUBLE,
  sale_date DATE
) USING DELTA
PARTITIONED BY (sale_date);

-- Query that triggers Partition Pruning
SELECT sum(amount)
FROM sales
WHERE sale_date = '2024-01-01'; -- Skips all other
```

Partitioning

Over Partitioning

The trap — over-partitioning:

- Partitioning by high-cardinality columns (e.g., user_id, timestamp, order_id)
- **Result**: thousands of tiny directories containing tiny files
- **Impact**: severe metadata overhead (driver node bottleneck) and loss of compression efficiency

Typical symptoms:

- Many partitions containing **1–10 files**
- File sizes < 32 MB
- Query plan showing **hundreds of partitions scanned**
- OPTIMIZE is taking hours because the data is too fragmented

Partitioning

How to Avoid Over-Partitioning

General recommendations:

- Partition only by **low- or medium-cardinality** columns (e.g., date, country, category)
- Prefer **Z-ordering** or **Bloom filters** instead of “deep partitioning”
- If you have already over partitioned:
  - **Repartition** the table and rewrite it
  - Consolidate partitions (e.g., daily → monthly)

Rule of thumb:

- Partitions should generally contain at least **1 GB** of data
- If your table is small (< 1 TB), you might **not** need partitioning at all

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VACUUM

Keeping Tables Clean and Performant

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VACUUM

Problem

- UPDATE, DELETE, INSERT, and MERGE operations create new files
- Old files increase the table size
- When your tables are large, you have poor read performance

VACUUM

Solution

- VACUUM operation — removes old unused parquet files

vacuum.sql

```
-- Run VACUUM against table_name
VACUUM table_name [RETAIN num HOURS];
```

VACUUM

Solution

Retention period:

- Default: 7 days (RETAIN 168 HOURS)
- Can be reduced (e.g., for dev environments): RETAIN 24 HOURS
- Warning: too short → cannot time travel/rollback

vacuum.sql

```sql
-- Run VACUUM against table_name
VACUUM table_name [RETAIN num HOURS];
```

VACUUM

Impact on Table Size & Performance

Effects of VACUUM:

- Reduces table size on disk
- Speeds up table scans
- Reduces cluster workload during reads

Tips:

- Run VACUUM after large updates/deletes
- Avoid running too frequently to preserve history

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Statistics & Data Skipping

Query Faster Without Full Scans

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Statistics & Data Skipping

File-Level Statistics

Delta Lake stores metadata for every data file:

- Min/max values per column
- Number of records
- Null counts
- Partition information (if applicable)

Why this matters:

- The client can understand the data distribution **without** opening the file
- Enables smarter, more targeted reading

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Statistics & Data Skipping

rdryn — admin@bozon: ~/projects/delta-lake-definitive-guide — ssh admin@192.168.0.10 — 123×32


```
\"fips\":1001,\"cases\":0,\"deaths\":0},\"maxValues\":{\"date\":\"2021-01-10\",\"county\":\"Ziebach\",\"state\":\"Wyoming\"
,\"fips\":78030,\"cases\":920560,\"deaths\":25562},\"nullCount\":{\"date\":0,\"county\":0,\"state\":0,\"fips\":1262,\"cases
\":0,\"deaths\":3588}}"
  }
}
{
  "add": {
    "path": "part-00006-d0ec7722-b30c-4e1c-92cd-b4fe8d3bb954-c000.snappy.parquet",
    "partitionValues": {},
    "size": 883342,
    "modificationTime": 1619121488000,
    "dataChange": true,
    "stats": "{\"numRecords\":147181,\"minValues\":{\"date\":\"2021-01-10\",\"county\":\"Abbeville\",\"state\":\"Alabama\",
\"fips\":1001,\"cases\":0,\"deaths\":0},\"maxValues\":{\"date\":\"2021-02-25\",\"county\":\"Ziebach\",\"state\":\"Wyoming\"
,\"fips\":78030,\"cases\":1188101,\"deaths\":29025},\"nullCount\":{\"date\":0,\"county\":0,\"state\":0,\"fips\":1250,\"case
s\":0,\"deaths\":3510}}"
  }
}
{
  "add": {
    "path": "part-00007-4582392f-9fc2-41b0-ba97-a74b3afc8239-c000.snappy.parquet",
    "partitionValues": {},
    "size": 325440,
    "modificationTime": 1619121487000,
    "dataChange": true,
    "stats": "{\"numRecords\":47559,\"minValues\":{\"date\":\"2021-02-25\",\"county\":\"Abbeville\",\"state\":\"Alabama\",\
"fips\":1001,\"cases\":0,\"deaths\":0},\"maxValues\":{\"date\":\"2021-03-11\",\"county\":\"Ziebach\",\"state\":\"Wyoming\",
\"fips\":78030,\"cases\":1208672,\"deaths\":30068},\"nullCount\":{\"date\":0,\"county\":0,\"state\":0,\"fips\":408,\"cases\
":0,\"deaths\":1170}}"
  }
}
admin@bozon:~/projects/delta-lake-definitive-guide$
```

Statistics & Data Skipping

```
rdryn — admin@bozon: ~/projects — ssh admin@192.168.0.10 — 123×32
Zellij (fascinating-brachiosaur)  Tab #1                                  Alt <[]>  VERTICAL
```


```
admin@bozon: ~/projects/delta-lake-definitive-guide —— 0
    "dataChange": true,
    "stats": "{\"numRecords\":147181,\"minValues\":{\"date\"
:\"2021-01-10\",\"county\":\"Abbeville\",\"state\":\"Alabama
\",\"fips\":1001,\"cases\":0,\"deaths\":0},\"maxValues\":{\"
date\":\"2021-02-25\",\"county\":\"Ziebach\",\"state\":\"Wyo
ming\",\"fips\":78030,\"cases\":1188101,\"deaths\":29025},\"
nullCount\":{\"date\":0,\"county\":0,\"state\":0,\"fips\":12
50,\"cases\":0,\"deaths\":3510}}"
  }
}
{
  "add": {
    "path": "part-00007-4582392f-9fc2-41b0-ba97-a74b3afc8239
-c000.snappy.parquet",
    "partitionValues": {},
    "size": 325440,
    "modificationTime": 1619121487000,
    "dataChange": true,
    "stats": "{\"numRecords\":47559,\"minValues\":{\"date\":
\"2021-02-25\",\"county\":\"Abbeville\",\"state\":\"Alabama\
",\"fips\":1001,\"cases\":0,\"deaths\":0},\"maxValues\":{\"d
ate\":\"2021-03-11\",\"county\":\"Ziebach\",\"state\":\"Wyom
ing\",\"fips\":78030,\"cases\":1208672,\"deaths\":30068},\"n
ullCount\":{\"date\":0,\"county\":0,\"state\":0,\"fips\":408
,\"cases\":0,\"deaths\":1170}}"
  }
}
admin@bozon:~/projects/delta-lake-definitive-guide$
```



```
admin@bozon: ~/projects/delta-lake-definitive-guide —— 0
{
  "numRecords": 47559,
  "minValues": {
    "date": "2021-02-25",
    "county": "Abbeville",
    "state": "Alabama",
    "fips": 1001,
    "cases": 0,
    "deaths": 0
  },
  "maxValues": {
    "date": "2021-03-11",
    "county": "Ziebach",
    "state": "Wyoming",
    "fips": 78030,
    "cases": 1208672,
    "deaths": 30068
  },
  "nullCount": {
    "date": 0,
    "county": 0,
    "state": 0,
    "fips": 408,
    "cases": 0,
    "deaths": 1170
  }
}
admin@bozon:~/projects/delta-lake-definitive-guide$
```


```
Ctrl + <g> LOCK  <p> PANE  <t> TAB  <n> RESIZE  <h> MOVE  <s> SEARCH  <o> SESSION  <q> QUIT  ...
```

Statistics & Data Skipping

Data Skipping Means Client Avoids Reading Files That Cannot Satisfy the Query

How it works:

- Client reads delta metadata (stats)
- Compares stats with query filters
- Only loads files whose min/max **overlaps** with the filter

Result:

- Fewer files scanned
- Less I/O
- Faster queries

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Statistics & Data Skipping

Data Skipping Means Client Avoids Reading Files That Cannot Satisfy the Query

What the client does:

- Checks file stats (min/max event_date)
- Skips all files where **max < '2023-06-01'**
- Reads only relevant files instead of scanning the whole table

Impact:

- Significant reduction in scanned data
- Lower latency
- Better cluster utilization

filter.sql

```sql
SELECT *
FROM events
WHERE event_date >= '2023-06-01';
```

Z-Ordering

Improving Multi-Column Filters

Z-Ordering

What Is Z-Ordering?

Z-Ordering is a data clustering algorithm:

- Reorders data within Delta files
- Groups related column values close together on disk
- Uses a space-filling “Z-curve” to interleave bits from multiple columns

Goal:

- Make multi-column filtering faster by improving data locality

Z-Ordering

Why Z-Ordering?

Benefits:

- Reduces the number of files a client needs to scan
- More efficient data skipping
- Works best for **high-cardinality columns** (e.g., user_id, timestamp)
- Particularly effective for multi-column predicates:

z-curve.sql

```sql
WHERE user_id = X AND event_date BETWEEN ...
```

Z-Ordering

How Z-Order Helps

Without Z-order:

- Data for user_id and event_date is spread across many files, which means poor locality
- Client scans many files just to find a small subset of rows

With Z-order:

- Related values of user_id + event_date are co-located in fewer files
- The client can skip most files

Result:

- Significant improvements in selective queries

Z-Ordering

How Z-Order Helps

Scenario:

- You have a user events table

Columns:

- user_id — high-cardinality identifier
- event_date — timestamp/date
- event_type — string (e.g., "click", "view", etc.)
- session_id
- country
- device_type

example.sql

```
SELECT *
FROM events
WHERE
    user_id = '65e1419e-59db-4c5e-9914-b69361bac2fb' AND
    event_date BETWEEN '2025-05-01' AND '2025-06-01';
```

Query pattern:

- Most queries filter by a combination of user_id and event_date

Z-Ordering

How Z-Order Helps

Without Z-order:

- Rows for the same user_id are spread across many files
- Date ranges overlap across files unpredictably
- The client must scan **hundreds** of files

With Z-order on (user_id, event_date):

- Rows for each user_id become physically close together
- Their dates fall into tight ranges
- The client can skip most files

z-curve-table-optimization-2.sql

```sql
-- Optimize table_name by user_id and event_date
OPTIMIZE events ZORDER BY (user_id, event_date);
```

Notes:

- Often combined with **OPTIMIZE** to compact small files and then apply Z-order
- Works best when you Z-order the columns most used together in filters
- Not necessary for partitioned columns

Bloom Filter Index

Fast Lookups on High-Cardinality Columns

Bloom Filter Index

Why Bloom Filters?

Use case:

- Columns with **high cardinality** (UUIDs, emails, session IDs, order IDs)
- Traditional data skipping (min/max stats) doesn't help for these columns
- Bloom filters give a fast, space-efficient way to check "**might** contain this value?"

Result:

- Avoids scanning files that do **not** contain the value

Bloom Filter Index

Bloom Filter = Probabilistic Index

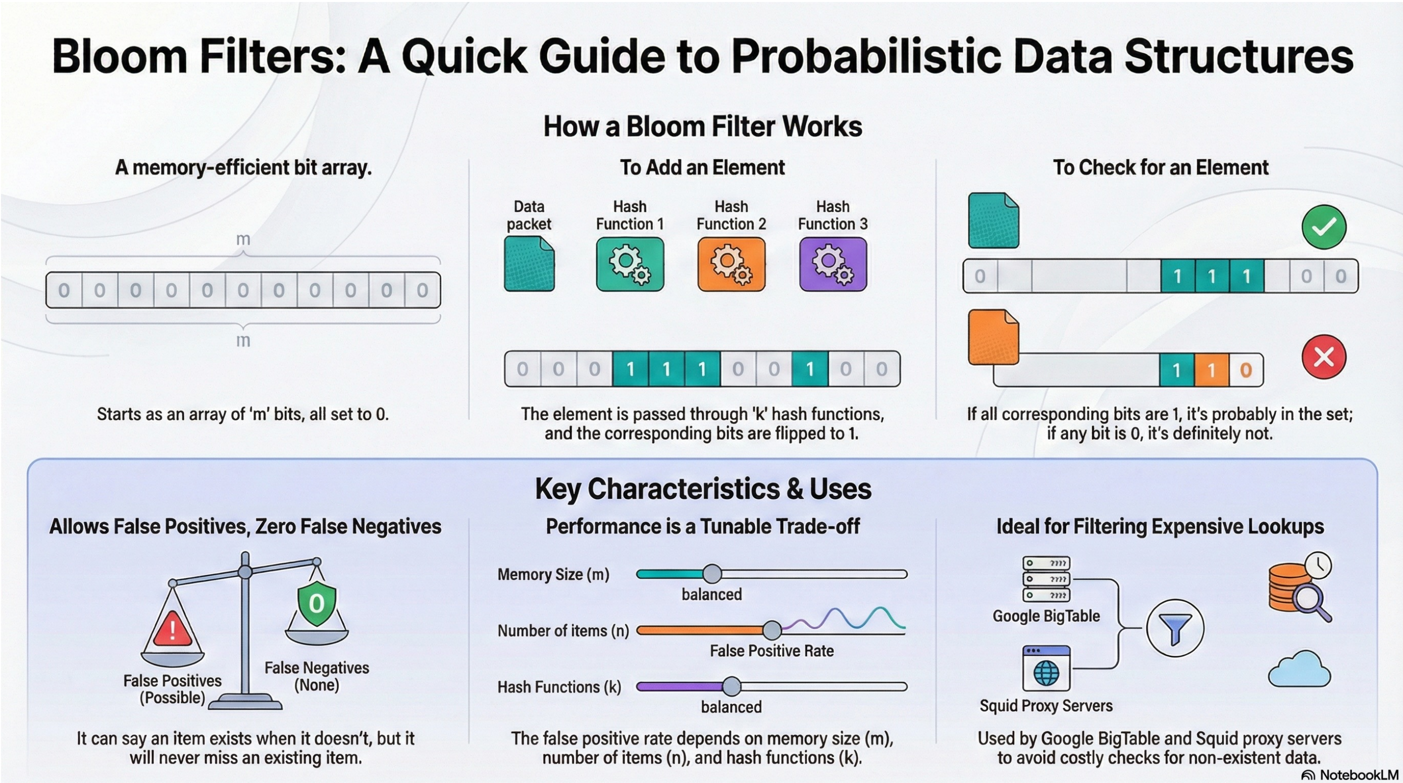
Benefits:

- Very compact bit array + multiple hash functions
- Can answer:
  - **“Definitely not present”**
  - **“Possibly present” (**false positives **possible**, false negatives **not** possible)

Why this helps:

- It is possible to check the Bloom filter **before** reading the file
- This eliminates large portion of irrelevant files → less I/O, faster reads

Bloom Filter Index



Bloom Filter Index

Example — UUID or Email Lookups

Consider a table:

- user_events

Columns:

- event_id (UUID)
- user_email (string)
- event_timestamp
- event_type

Bloom Filter Index

Example — UUID or Email Lookups

Without Bloom filters:

- UUIDs have no meaningful ordering
- min/max stats are useless
- Client may scan hundreds of files

bloom-filter.sql

```sql
SELECT *
FROM user_events
WHERE event_id = '550e8400-e29b-41d4-a716-446655440000';
```

Bloom Filter Index

Example — UUID or Email Lookups

With Bloom filter on event_id:

bloom-filrer-on-event-id.sql

```
ALTER TABLE user_events
ADD BLOOMFILTER INDEX
ON event_id
OPTIONS (fpp = 0.01, numItems = 1000000);
```

Bloom Filter Index

Example — UUID or Email Lookups

Effect:

- Client quickly checks each file's Bloom filter
- Most files are rejected immediately
- Only a few files are scanned

Moreover:

- Great for equality lookups on large, unique columns
- False positives are fine because it's still much faster than scanning
- Complements Z-order and statistics-based skipping
- **Small** index size means **low** overhead

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Liquid Clustering

Adaptive Layout for Fast Queries

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Liquid Clustering

Traditional Optimization Challenges

- Table management requires careful partition design
- Changing partition keys is expensive and often requires a full table rewrite
- Z-ordering needs continuous monitoring to match evolving query patterns
- Data skew: uneven distribution creates imbalanced partition sizes, which slows down queries

Liquid Clustering

What Is Liquid Clustering?

A new dynamic clustering strategy:

- Continuously maintains clustering as data evolves
- No need for expensive, full-table OPTIMIZE operations
- Automatically adapts as new data arrives or existing data changes
- It replaces partitioning and Z-ordering
- No more expensive rewrites

Idea:

- Instead of periodically “reorganizing everything,” the table stays well-organized over time
- The data is organized using clustering keys to optimize layout and simplify table management

Liquid Clustering

When to Use Liquid Clustering

- Frequent filtering on high-cardinality columns where partitioning fails
- Tables with data skew that need balanced distribution
- Fast-growing tables requiring constant tuning
- High-concurrency writes, where clustering reduces conflicts
- Changing query access patterns over time
- Cases where partitioning would create too many or too few partitions

Liquid Clustering

Enabling Liquid Clustering

- Add CLUSTER BY (<columns>) in CREATE TABLE for existing tables
- ALTER TABLE <name> CLUSTER BY (<columns>) for new tables
- Updates metadata only — does **not** rewrite existing data
- SQL, Python, and Scala APIs are all supported
- DataFrame API note: clustering keys can be set only at creation or with overwrite mode — not in append mode

Liquid Clustering

Enabling Liquid Clustering

Clustering is **incompatible** with traditional partitioning and ZORDER.
It is designed to **replace** both.

Liquid Clustering

Choosing Clustering Keys

Selecting the right keys is crucial — good keys maximize data skipping and boost query performance.

- **Filter-first**: choose columns most used in WHERE clauses and joins
- **Stats required**: keys must be among columns with collected statistics (first 32 by default)
- **Avoid redundancy**: skip highly correlated columns — pick just one
- **Up to 4 keys**: more can hurt performance on tables < 10 TB

Liquid Clustering

Automatic Liquid Clustering

How it works:

- **Workload analysis**: identifies the most frequently filtered columns
- **Adaptive optimization**: updates keys as query patterns or data distribution change
- **Cost-aware decisions**: picks new keys only when the benefit outweighs the re-clustering cost
- **Powered by predictive optimization**: runs asynchronously in the background

clustering.sql

```
CREATE OR REPLACE TABLE table1(column01 int, column02 string)
CLUSTER BY AUTO;
```

Liquid Clustering

Automatic Liquid Clustering

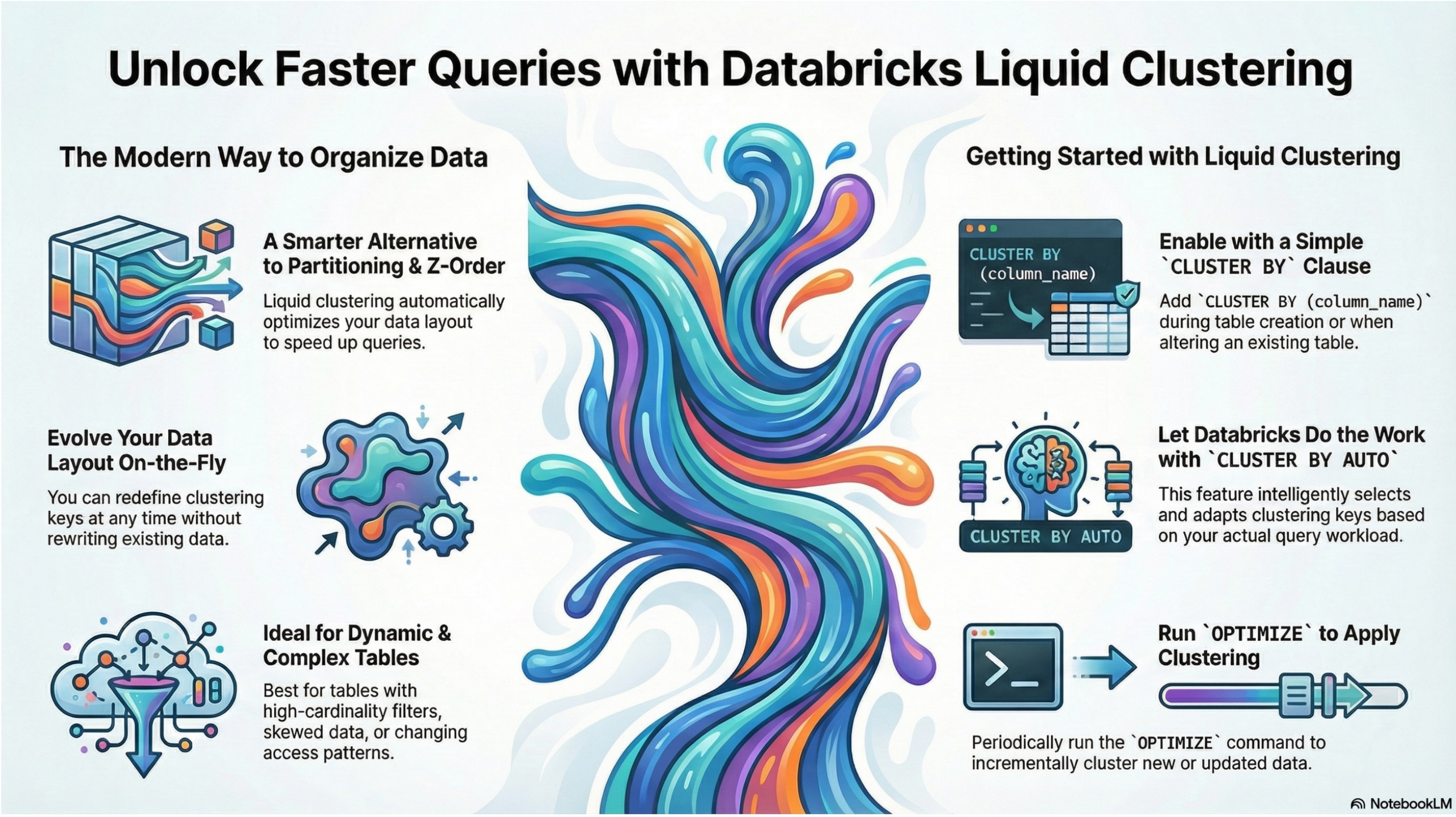
When keys may **not** be selected:

- The table is too small to benefit
- The existing layout is already effective
- Insufficient or inconsistent workload

Liquid Clustering

Key Benefits

- Stable performance without heavy maintenance jobs
- Faster queries with consistent data skipping
- Lower cost: avoids massive table rewrites
- Supports evolving datasets and dynamic clustering keys
- Redefine clustering keys without rewriting existing data is possible
- Simplify data layout: replaces manual partitioning and Z-order with one flexible technique
- Adapt to change: modify clustering keys without costly rewrites
- Automate with intelligence: automatic Liquid Clustering analyzes workloads and manages keys



Unlock Faster Queries with Databricks Liquid Clustering
The Modern Way to Organize Data
A Smarter Alternative to Partitioning & Z-Order
Liquid clustering automatically optimizes your data layout to speed up queries.
Evolve Your Data Layout On-the-Fly
You can redefine clustering keys at any time without rewriting existing data.
Ideal for Dynamic & Complex Tables
Best for tables with high-cardinality filters, skewed data, or changing access patterns.
Getting Started with Liquid Clustering
CLUSTER BY (column_name)
Enable with a Simple `CLUSTER BY` Clause
Add `CLUSTER BY (column_name)` during table creation or when altering an existing table.
CLUSTER BY AUTO
Let Databricks Do the Work with `CLUSTER BY AUTO`
This feature intelligently selects and adapts clustering keys based on your actual query workload.
Run `OPTIMIZE` to Apply Clustering
Periodically run the `OPTIMIZE` command to incrementally cluster new or updated data.
NotebookLM

Summary

Summary & Recommendations

Combine Techniques for Best Performance

- No single optimization solves everything — Delta works best when techniques are combined
- Start simple: partition → compact → Z-order
- Add Bloom for faster lookups on high-cardinality columns
- Run **VACUUM** regularly
- Migrate to Liquid Clustering (if possible) for large, frequently-updated tables
- Re-evaluate periodically as data volume grows

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Any Questions?

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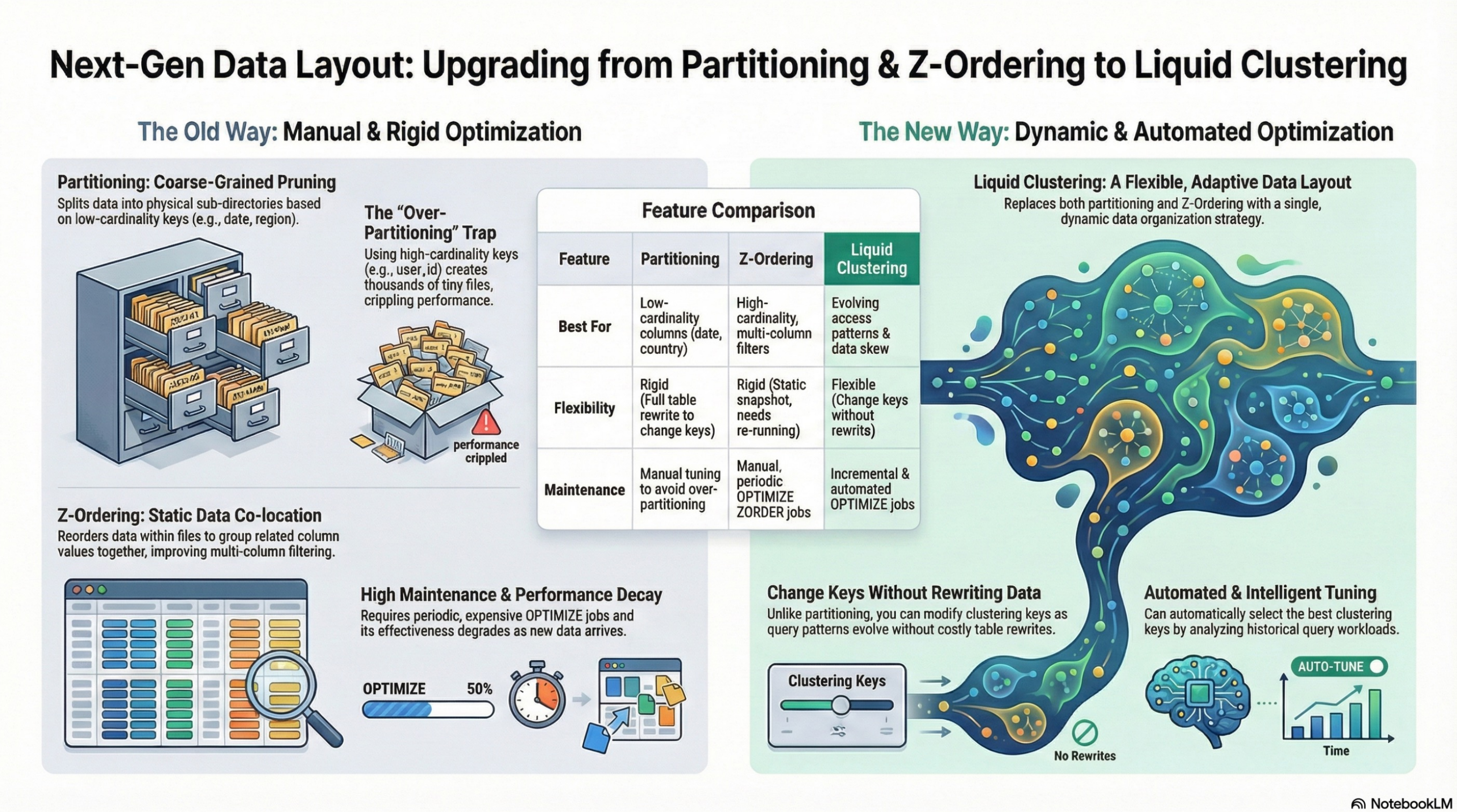
Next-Gen Data Layout: Upgrading from Partitioning & Z-Ordering to Liquid Clustering
The Old Way: Manual & Rigid Optimization
The New Way: Dynamic & Automated Optimization
Partitioning: Coarse-Grained Pruning
Splits data into physical sub-directories based on low-cardinality keys (e.g., date, region).
The "Over-Partitioning" Trap
Using high-cardinality keys (e.g., user_id) creates thousands of tiny files, crippling performance.
performance crippled
Z-Ordering: Static Data Co-location
Reorders data within files to group related column values together, improving multi-column filtering.
High Maintenance & Performance Decay
Requires periodic, expensive OPTIMIZE jobs and its effectiveness degrades as new data arrives.
OPTIMIZE
50%
Feature Comparison
Feature
Partitioning
Z-Ordering
Liquid Clustering
Best For
Low-cardinality columns (date, country)
High-cardinality, multi-column filters
Evolving access patterns & data skew
Flexibility
Rigid (Full table rewrite to change keys)
Rigid (Static snapshot, needs re-running)
Flexible (Change keys without rewrites)
Maintenance
Manual tuning to avoid over-partitioning
Manual, periodic OPTIMIZE ZORDER jobs
Incremental & automated OPTIMIZE jobs
Liquid Clustering: A Flexible, Adaptive Data Layout
Replaces both partitioning and Z-Ordering with a single, dynamic data organization strategy.
Change Keys Without Rewriting Data
Unlike partitioning, you can modify clustering keys as query patterns evolve without costly table rewrites.
Clustering Keys
No Rewrites
Automated & Intelligent Tuning
Can automatically select the best clustering keys by analyzing historical query workloads.
AUTO-TUNE
Time
NotebookLM

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FOR THE FUTURE

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