CS4221
Cloud Databases II. Data Lakes and Warehouses

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National University of Singapore
School of Computing

Data lakes and warehouses: outline

- Data lakes and warehouses
- Case studies
  - Snowflake
  - Other offerings

Recall cloud systems

- Vendors provide database-as-a-service (DBaaS) offerings that are managed DBMS environments.

- Newer systems are starting to blur the lines between shared-nothing and shared-disk.
  - Example: You can do simple filtering on Amazon S3 before copying data to compute nodes.

Recall cloud systems

Approach #1: **Managed DBMSs**

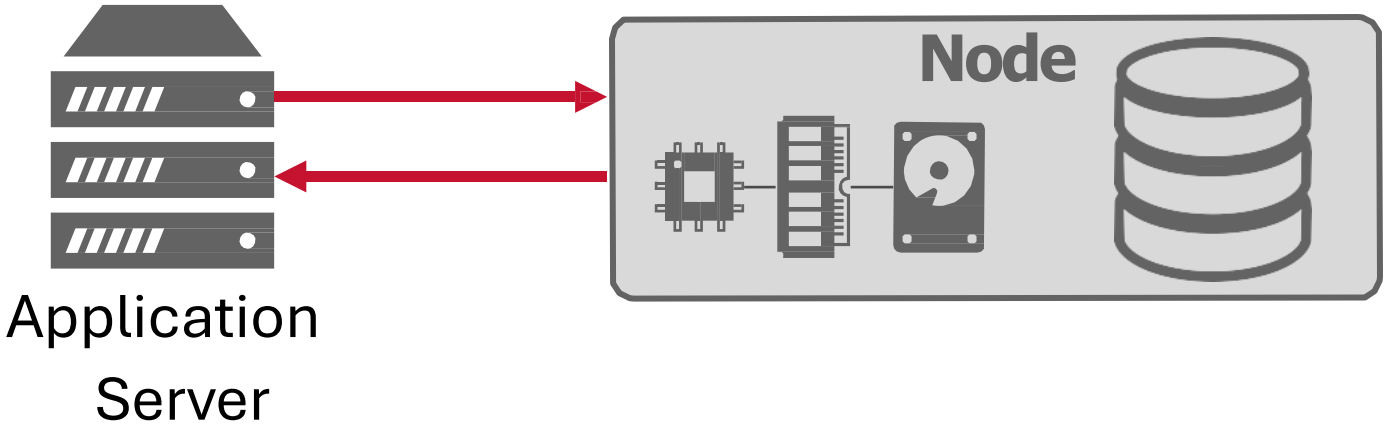
- No significant modification to the DBMS to be "aware" that it is running in a cloud environment.
- Examples: Most vendors

Approach #2: **Cloud-Native DBMS**

- System designed explicitly to run in a cloud environment.
- Usually based on a shared-disk architecture.
- Examples: Snowflake, Google BigQuery

Serverless databases

- Rather than always maintaining compute resources for each customer, a "serverless" DBMS evicts tenants when they become idle.



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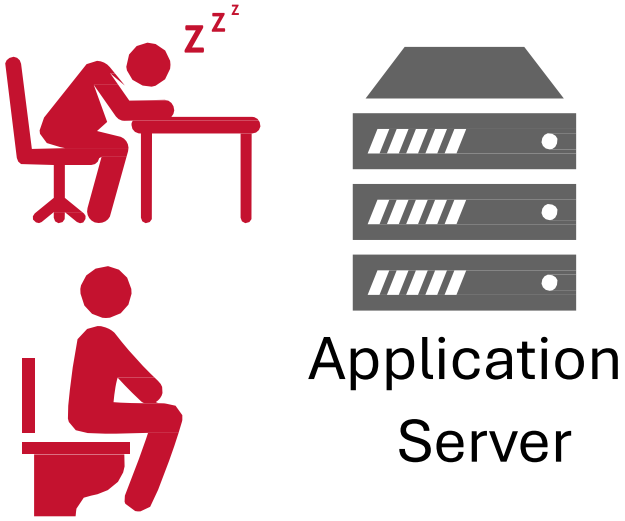

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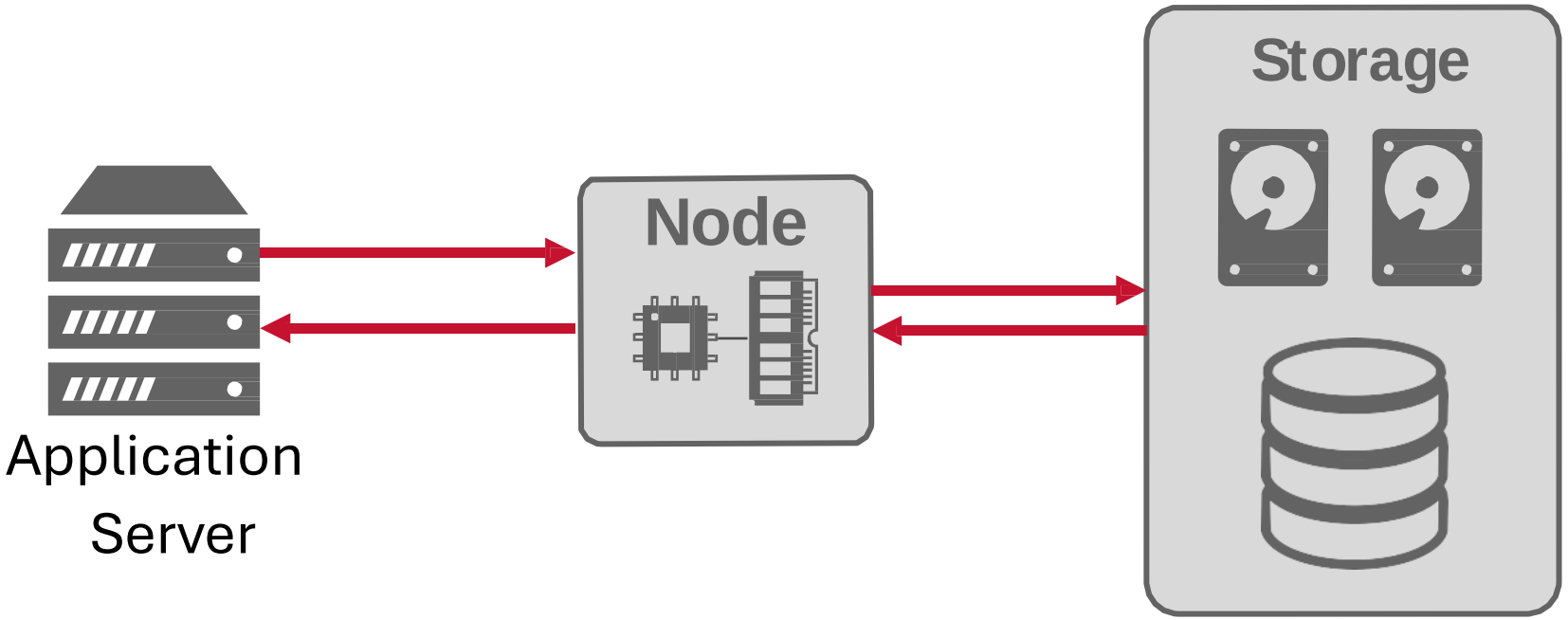

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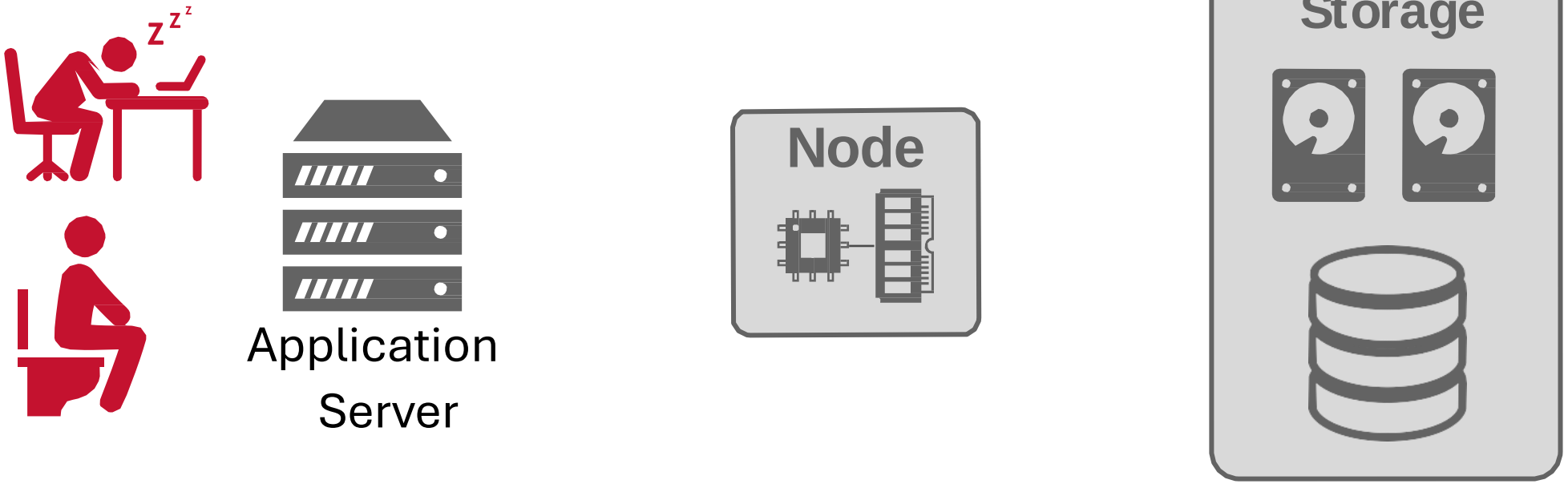

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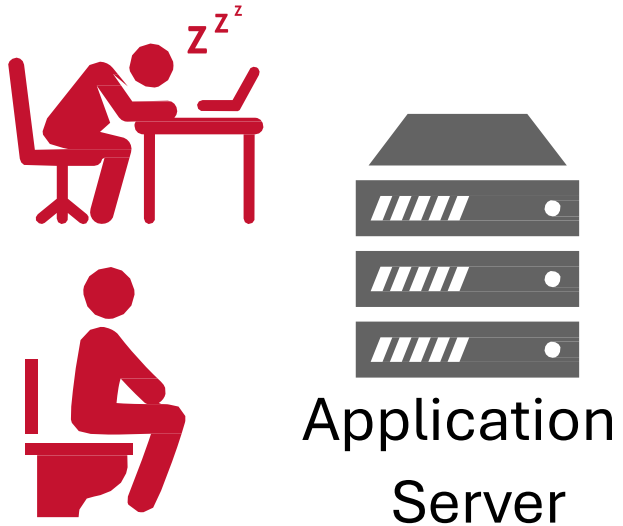

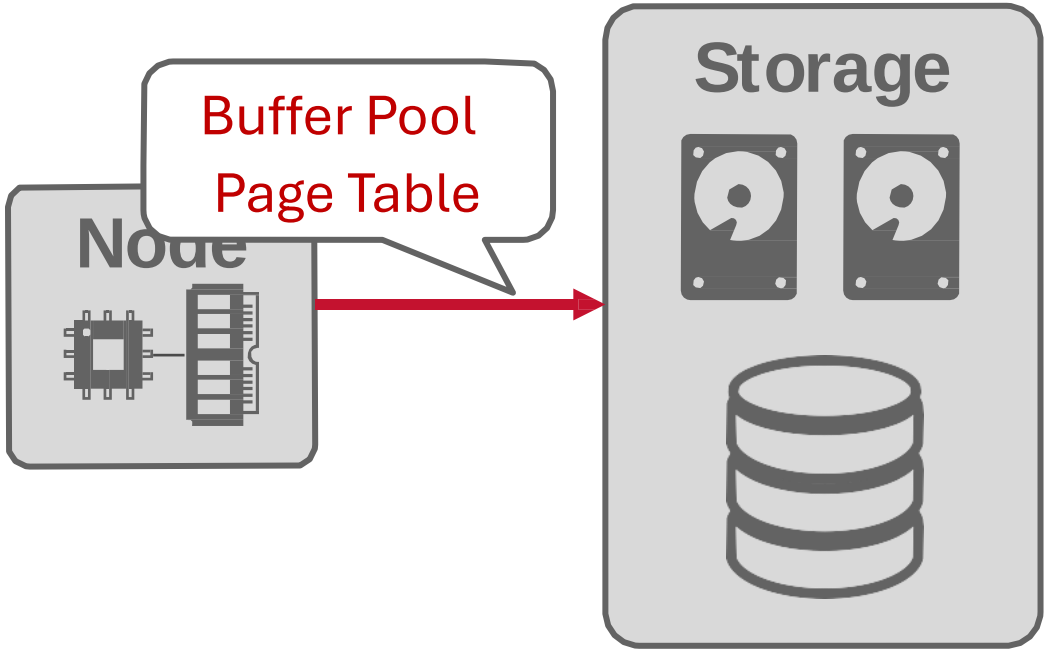

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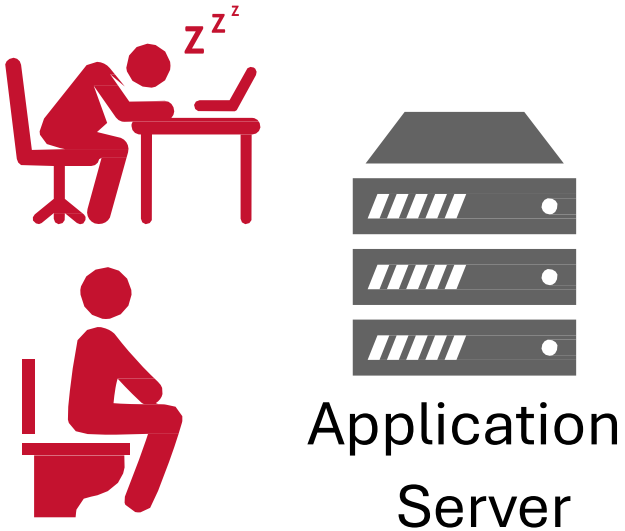

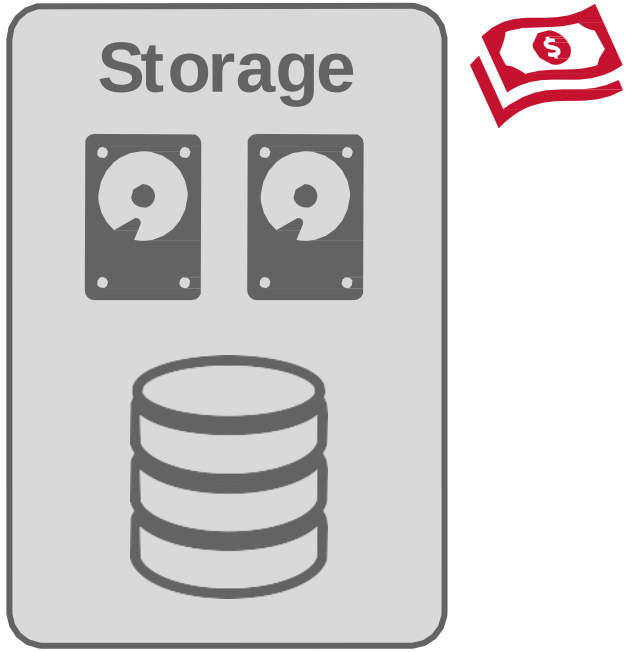

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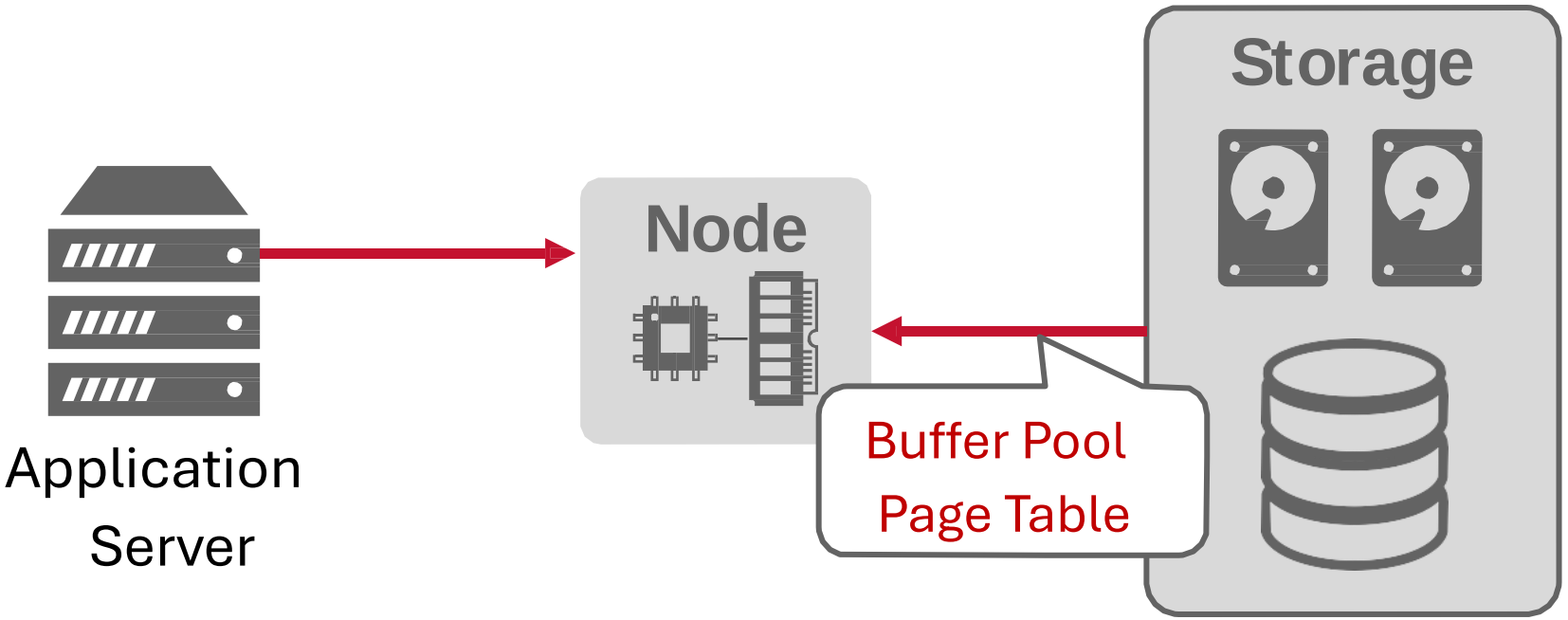
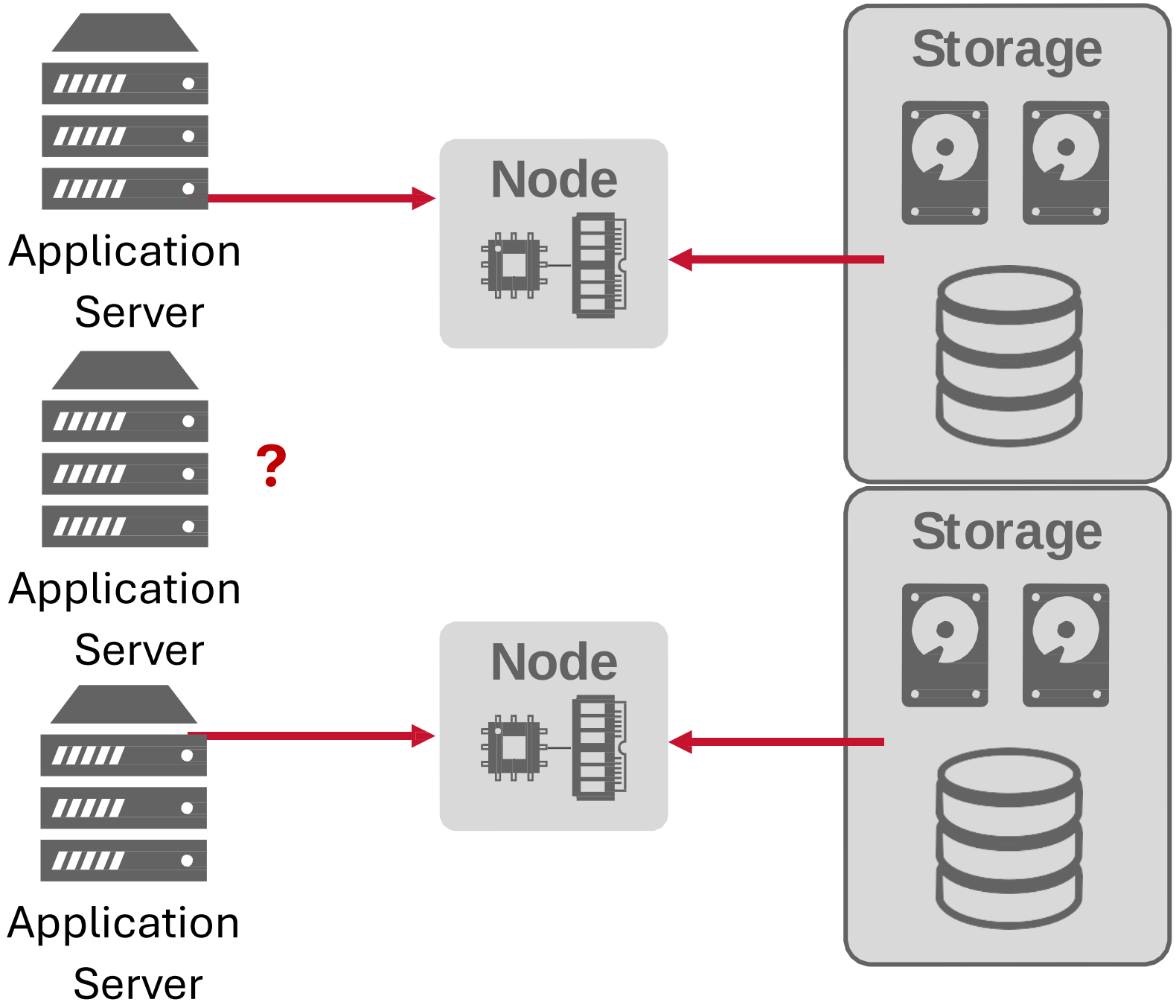
CockroachDB
NEON
amazon
fauna
Microsoft SQL Azure



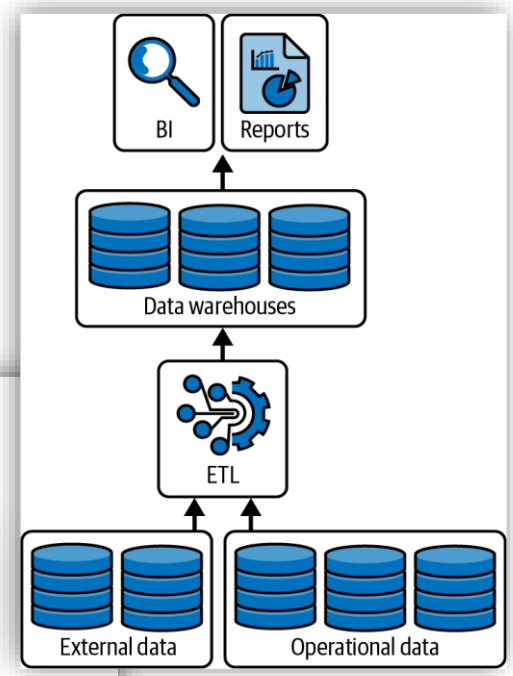
Overbooking?

- Sell more than have.



Data warehouses

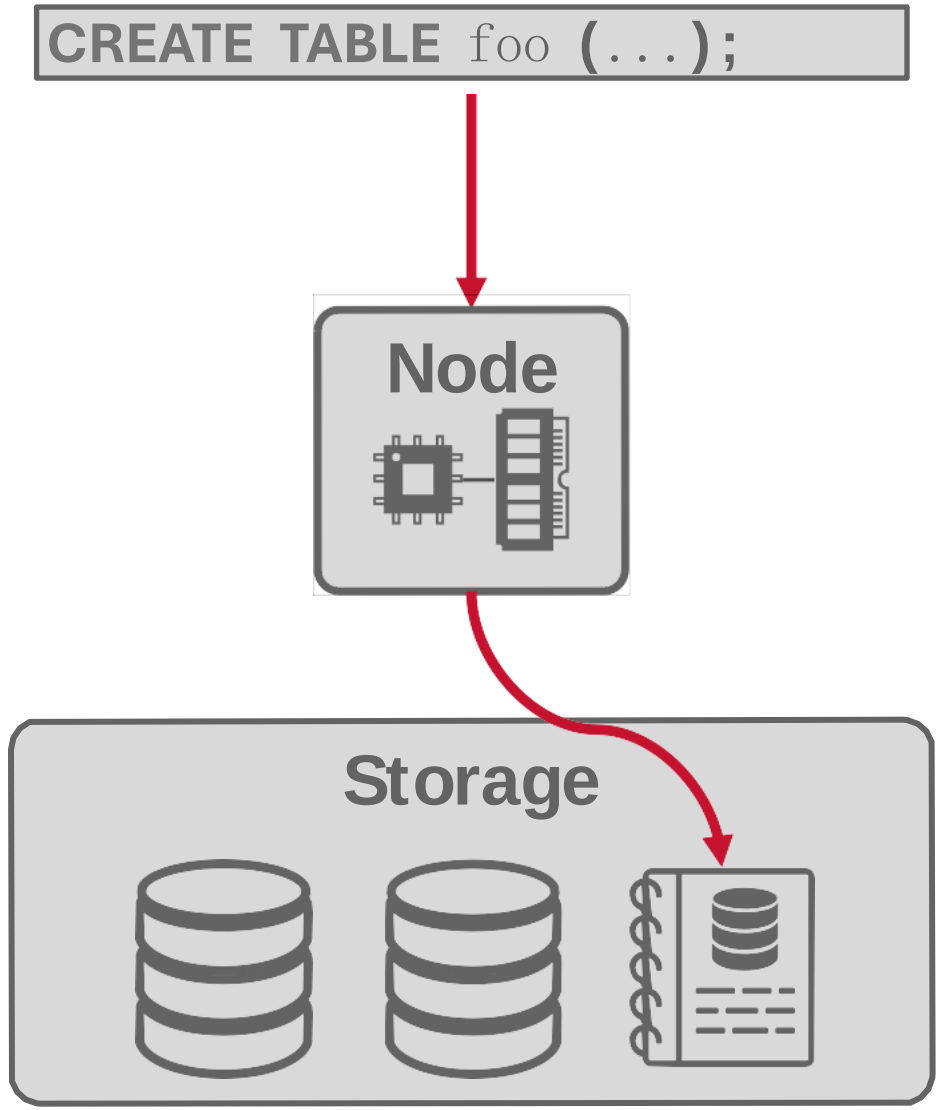
- A data management system that stores current and historical data from multiple sources in a business friendly manner for easier insights and reporting. Typically used for business intelligence (BI).
  - ACID transactions
  - Management features (backup and recovery controls, gated controls, etc.)
  - Performance optimizations (indexes, partitioning, etc.)
  - Limited support for ML and unstructured data.



https://www.future-processing.com/blog/top-8-data-warehouse-solutions/

Data lakes

- Repository for storing large amounts of structured, semi-structured, and unstructured data without having to define a schema or ingest the data into proprietary internal formats.



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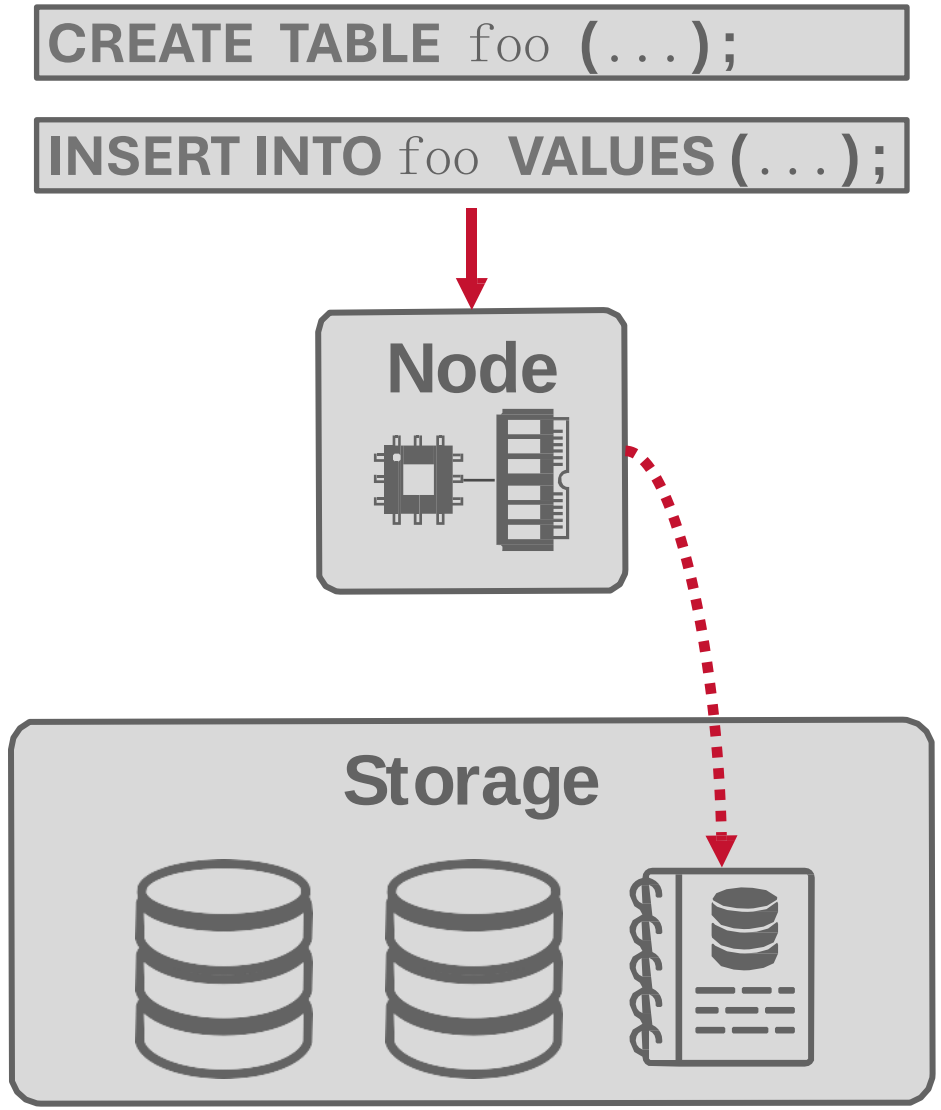

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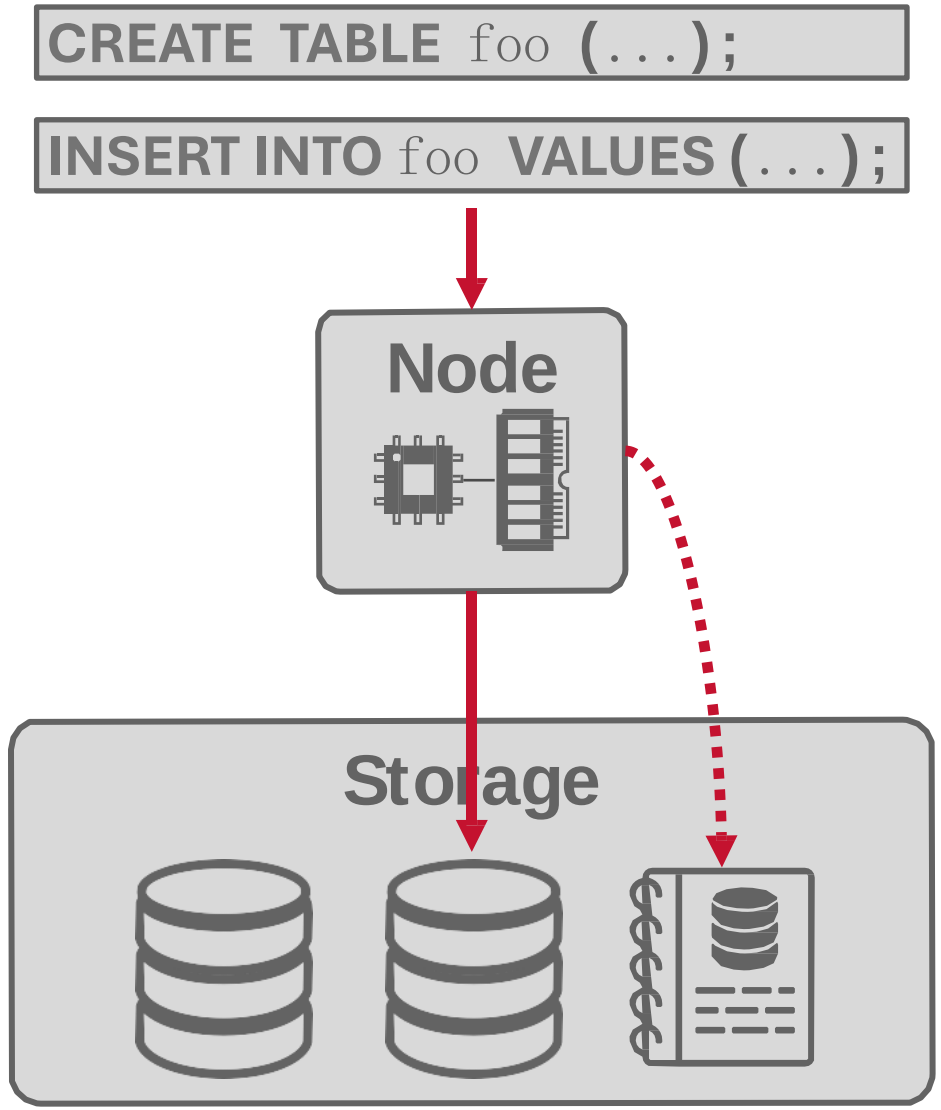

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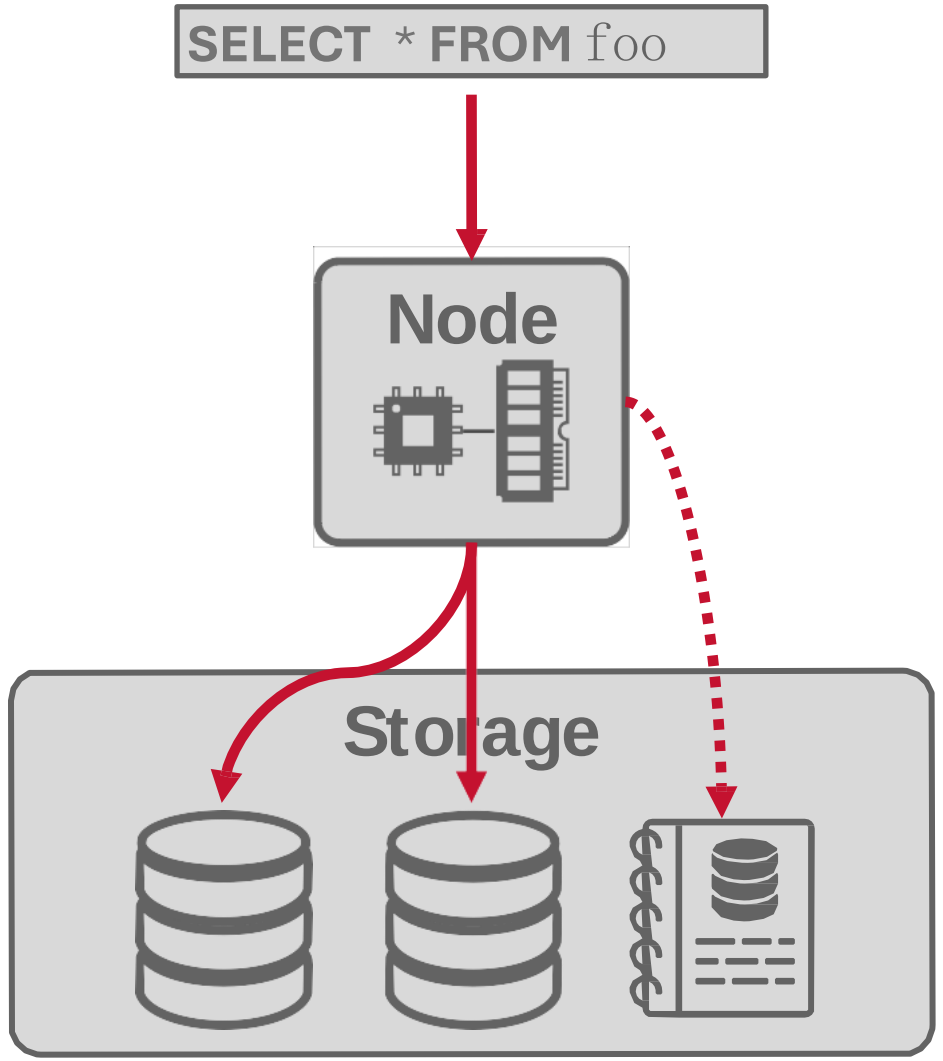

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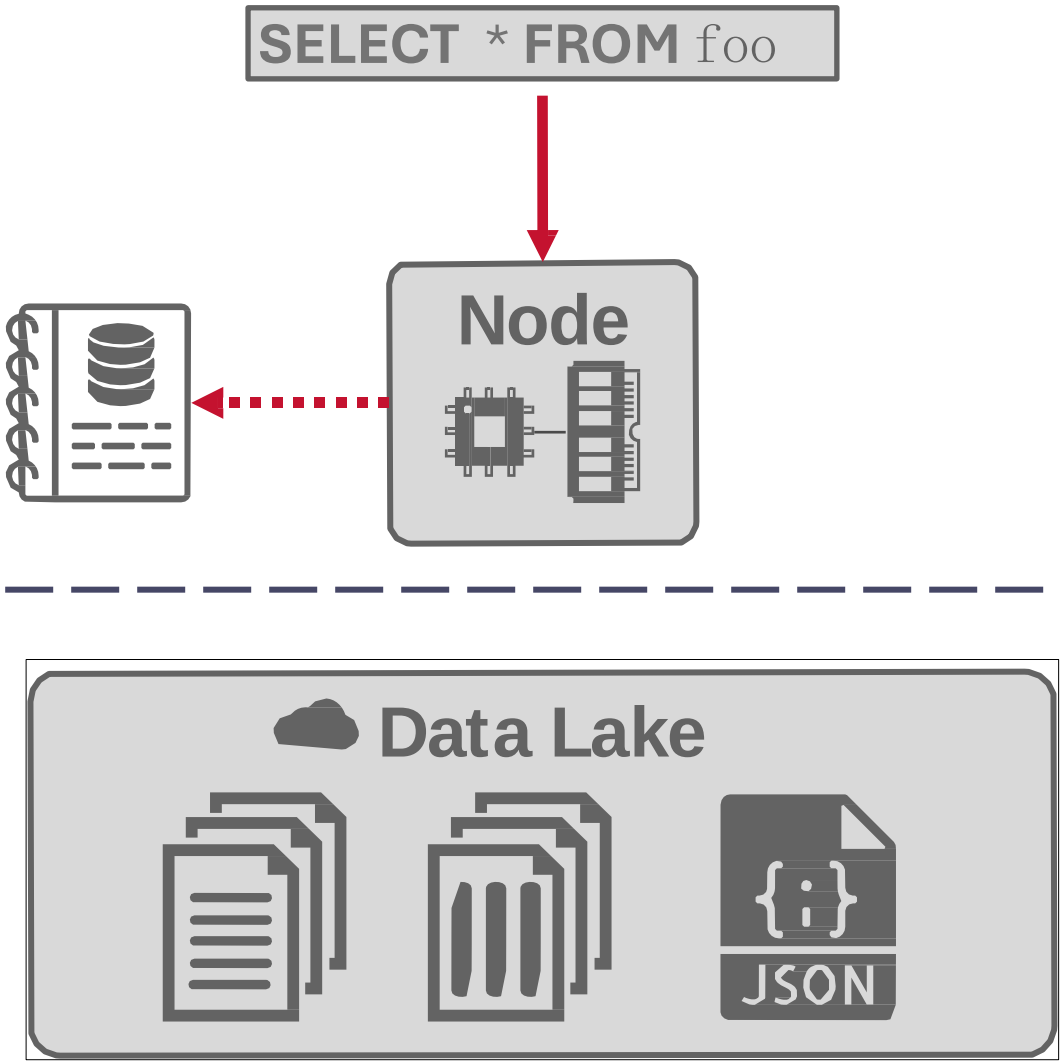

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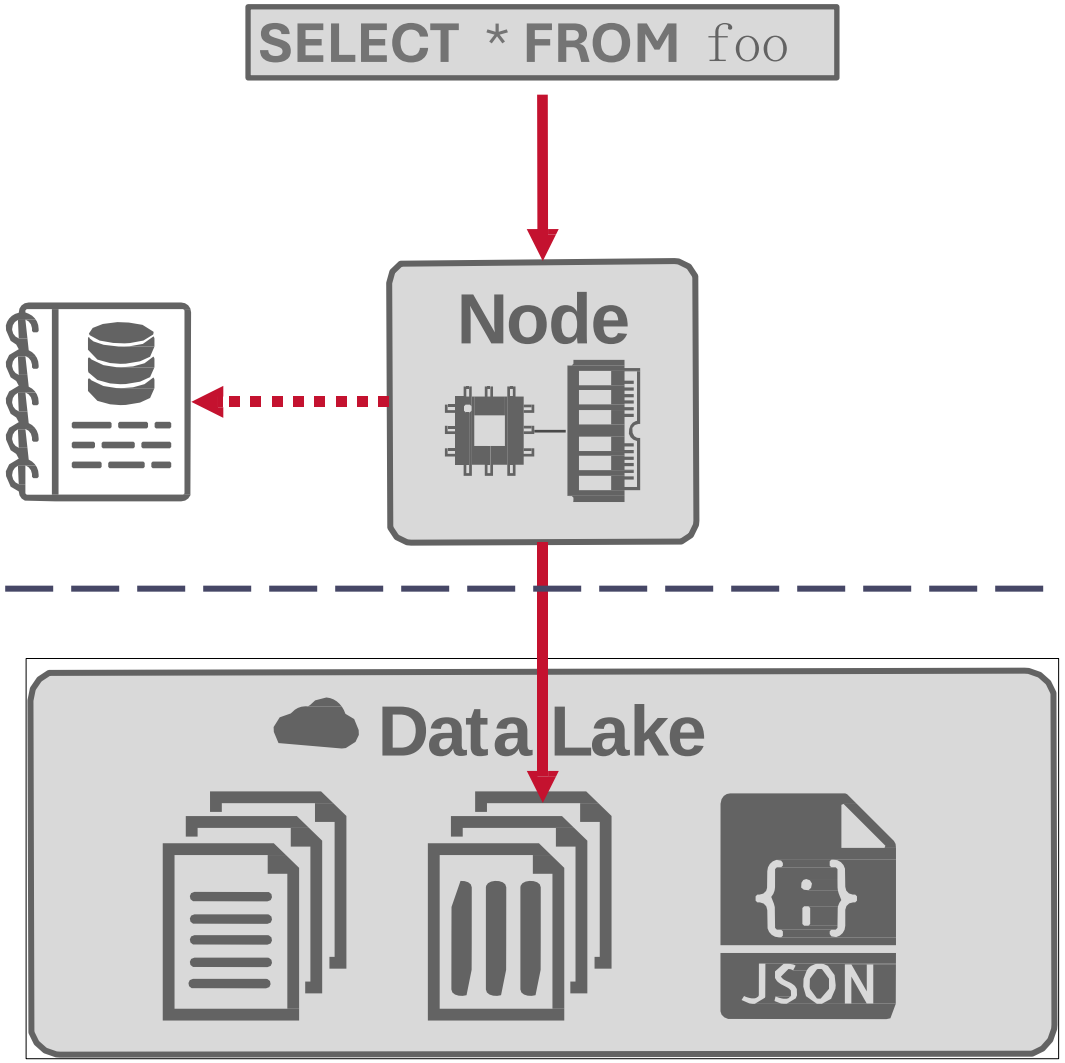


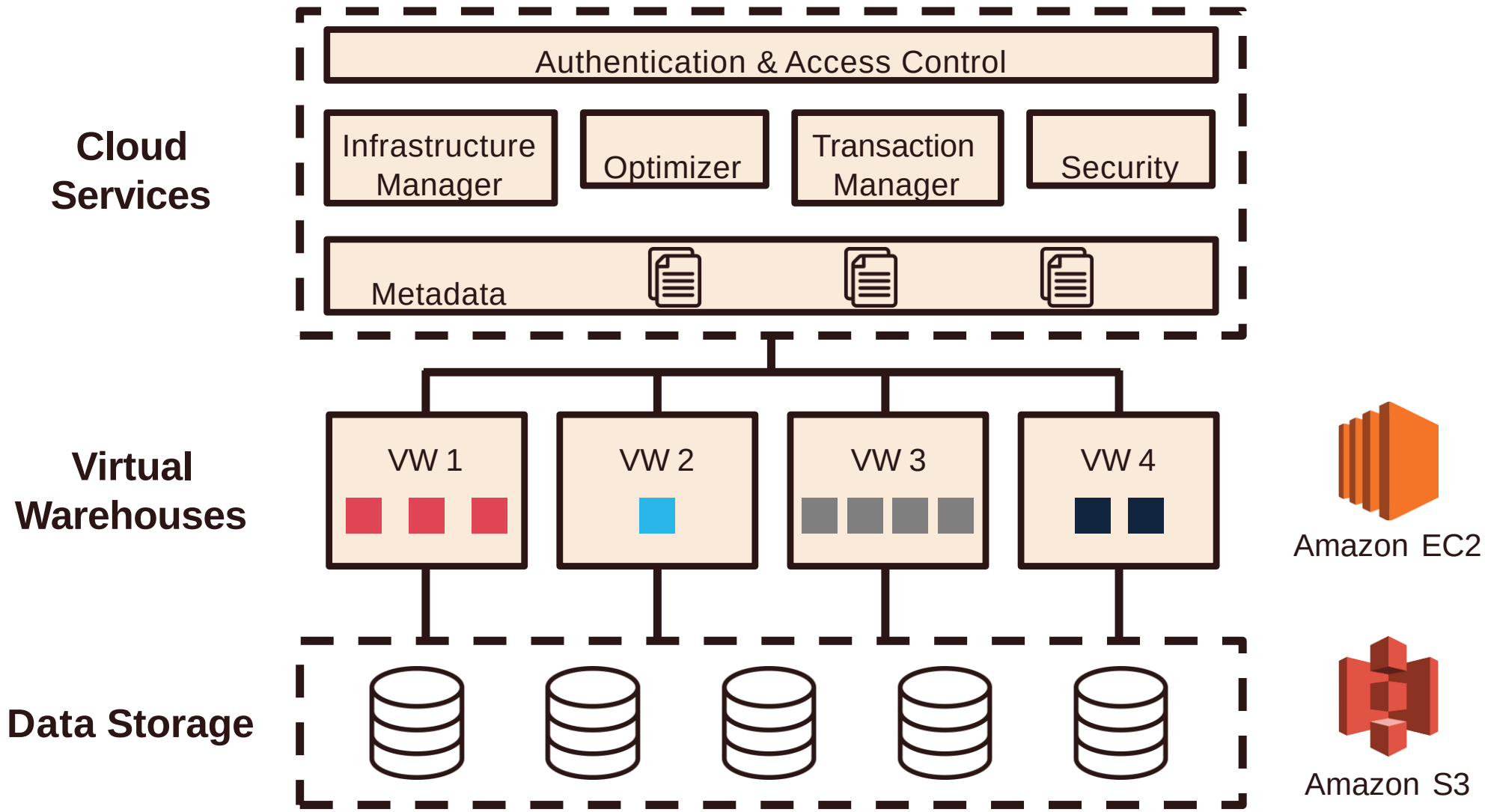
trino amazon REDSHIFT Google Big Query HIVE

databricks snowflake presto

Snowflake

- The Snowflake Elastic Data Warehouse
  - Target analytical queries to support business intelligence (BI)
  - Founded at 2012, growing fast, largest software IPO (2020) ever
- Pure SaaS
  - Nothing to install, always on, always up-to-date
  - Ease of use, only pay for what you use
- Multi-Cloud Support

Snowflake architecture



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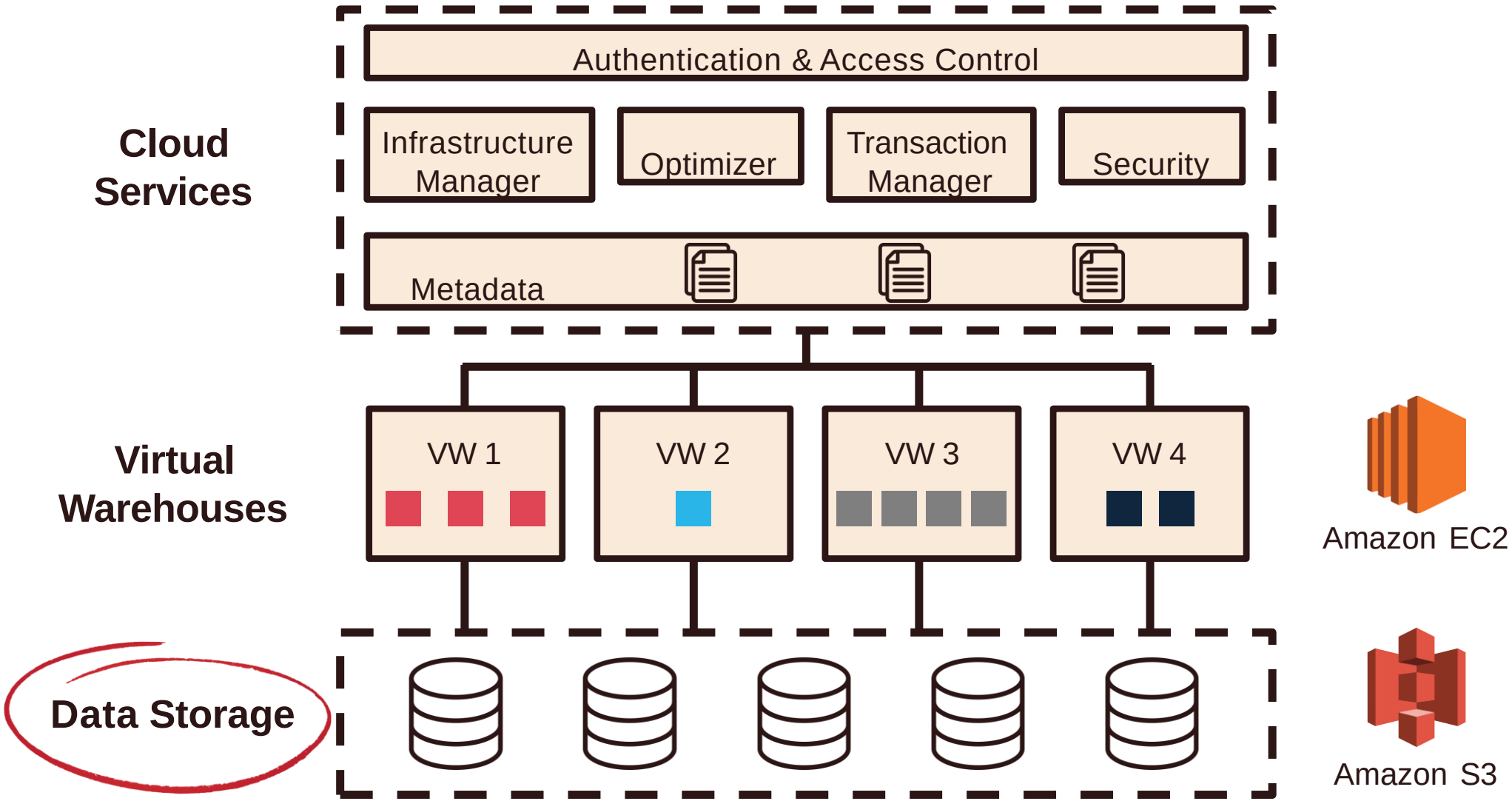


Recall from last lecture: storage models

Choice #1: N-ary Storage Model **(NSM)**

- This is for OLTP and what we learned before.

Choice #2: Decomposition Storage Model **(DSM)**

- This is for OLAP

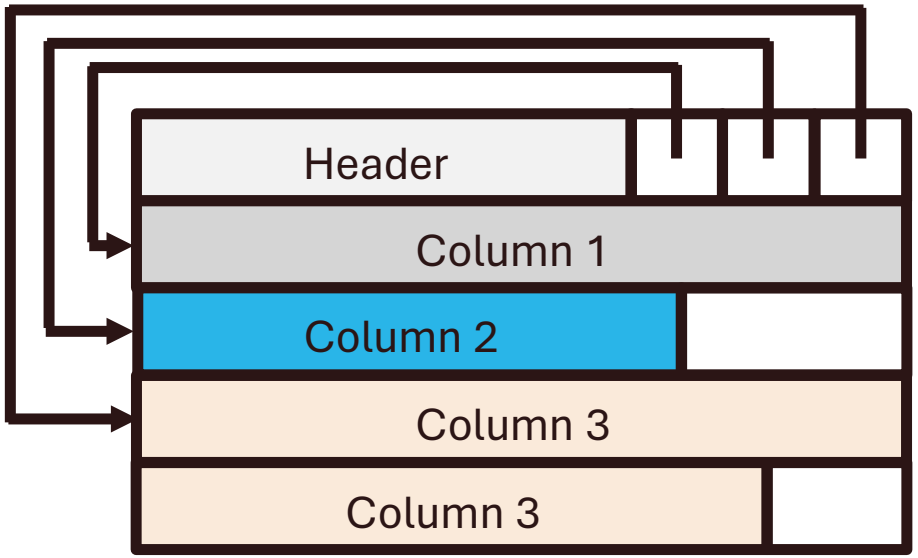
Choice #3: Hybrid Storage Model **(PAX)**

- This is for HTAP (Hybrid Transactional and Analytical Processing) and OLAP workloads.

Table file format

- Tables are horizontally partitioned
  - Micro-partition: size = 10s MB, natural ingestion order

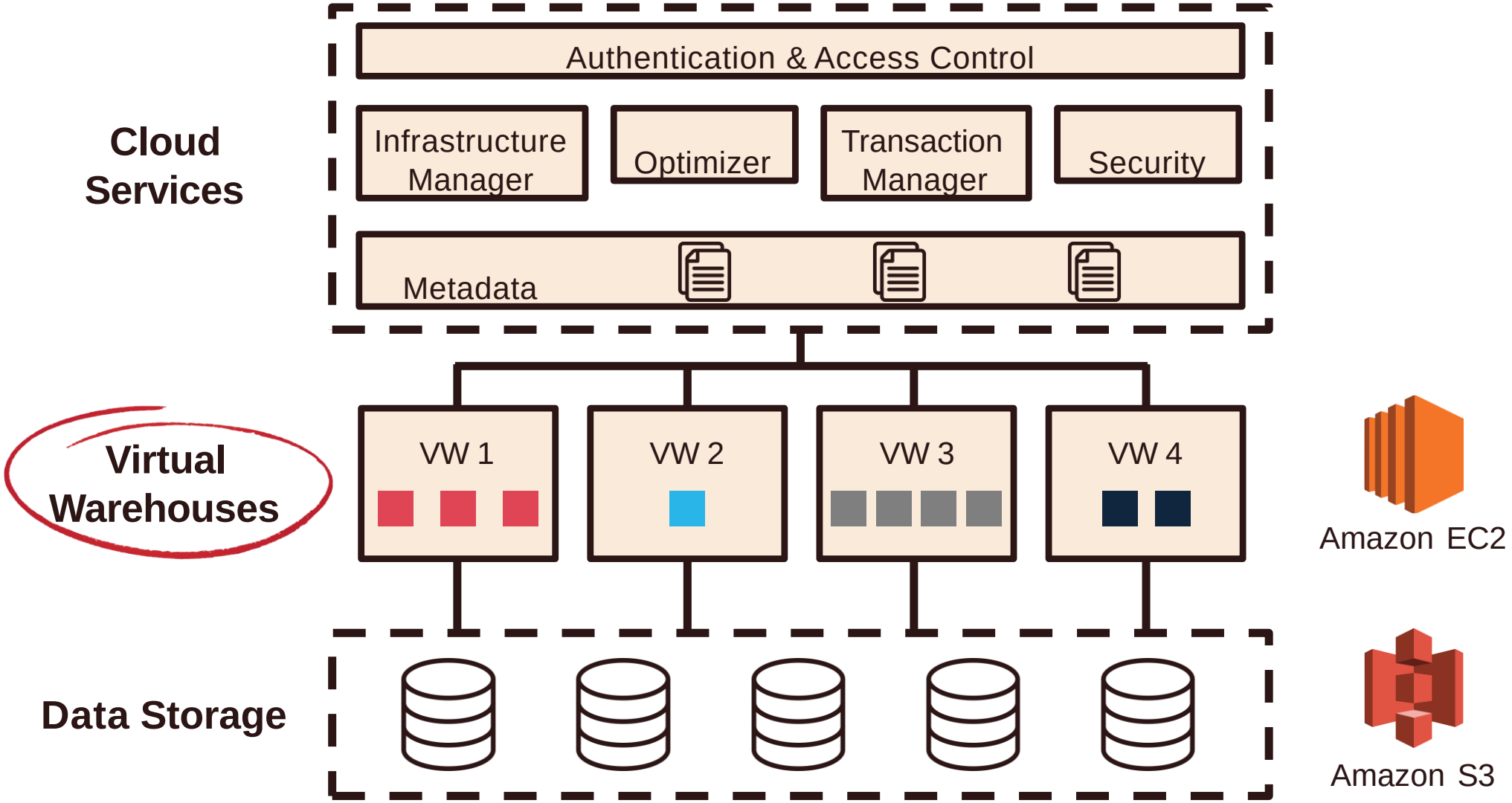
- Hybrid columnar (PAX) format



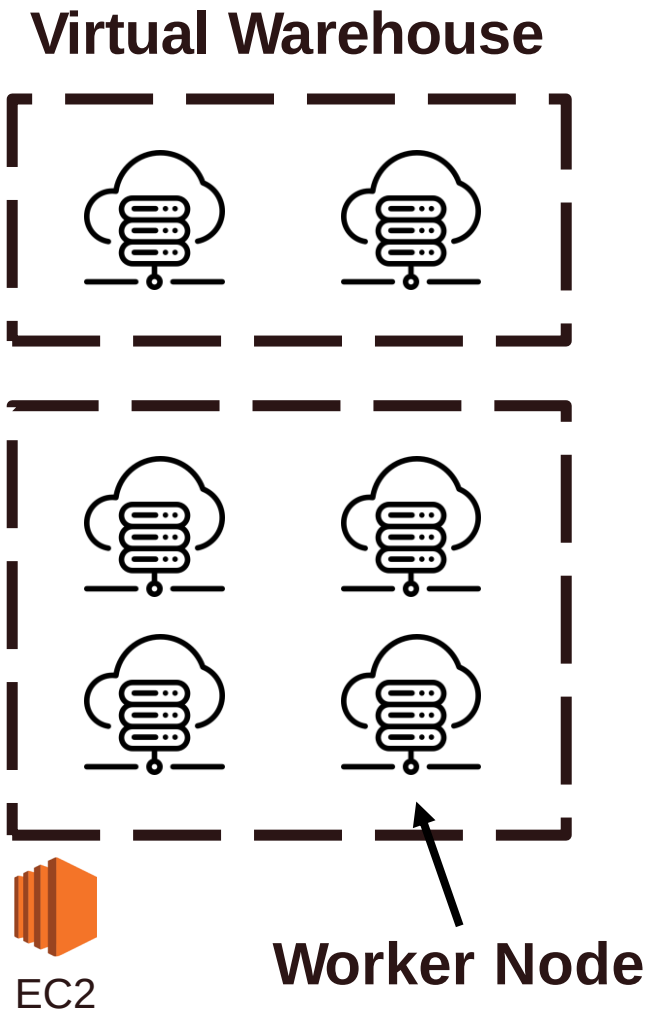
Queries first read header

Heavily Compressed

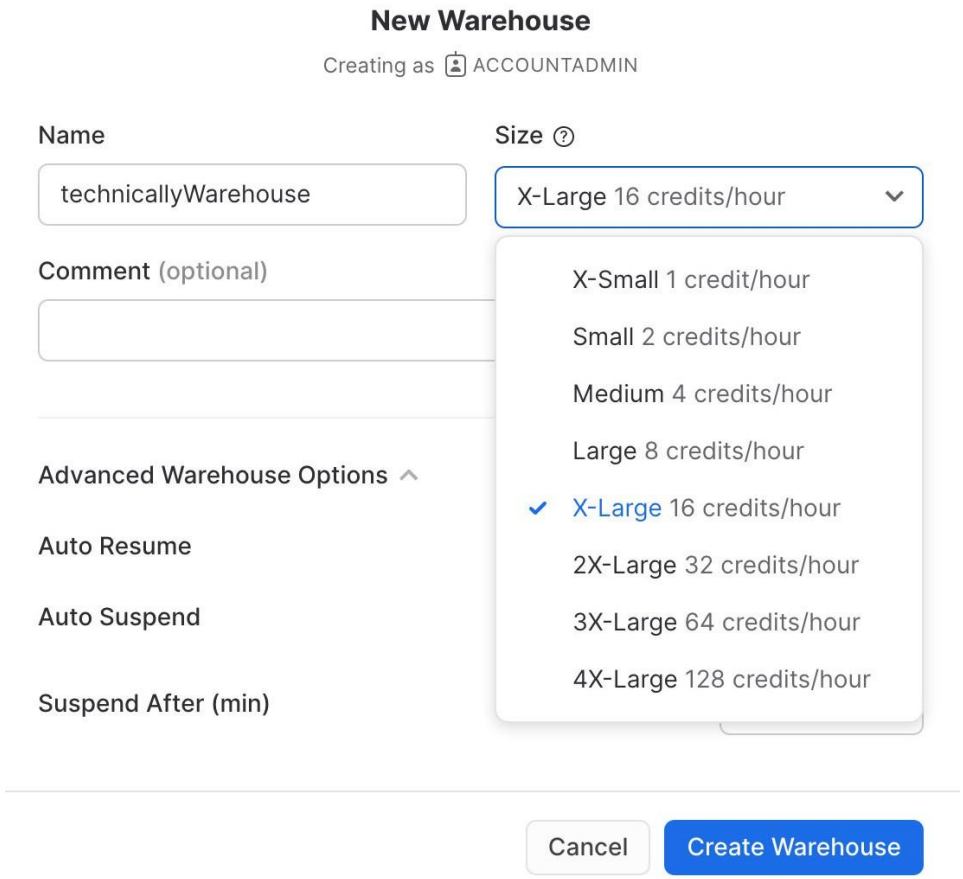
Snowflake architecture



Virtual warehouses: the muscle



- Create, destroy, resize on demand



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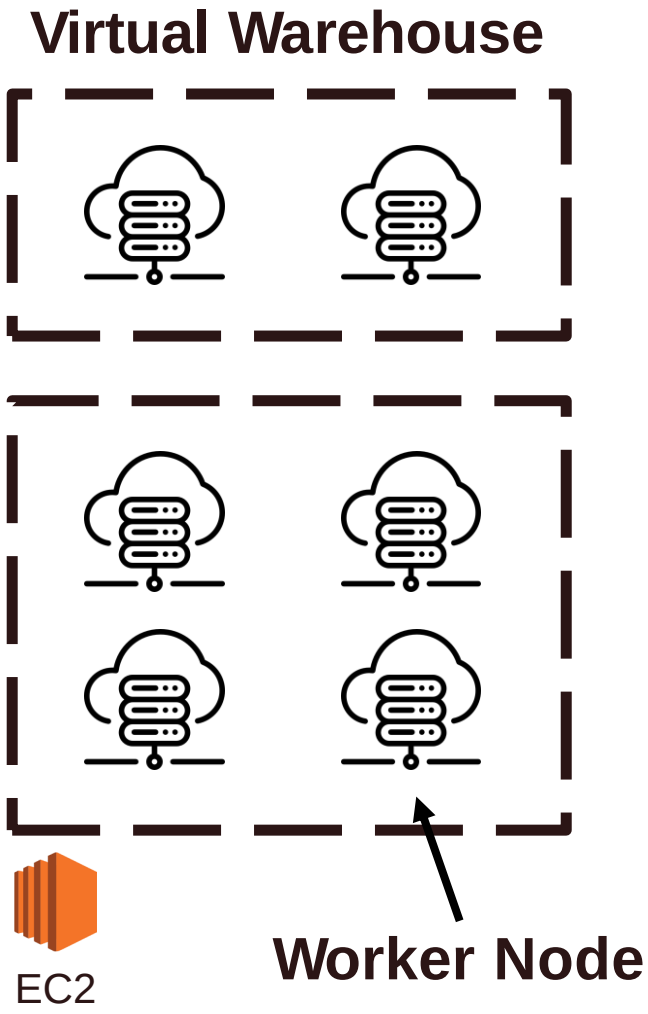


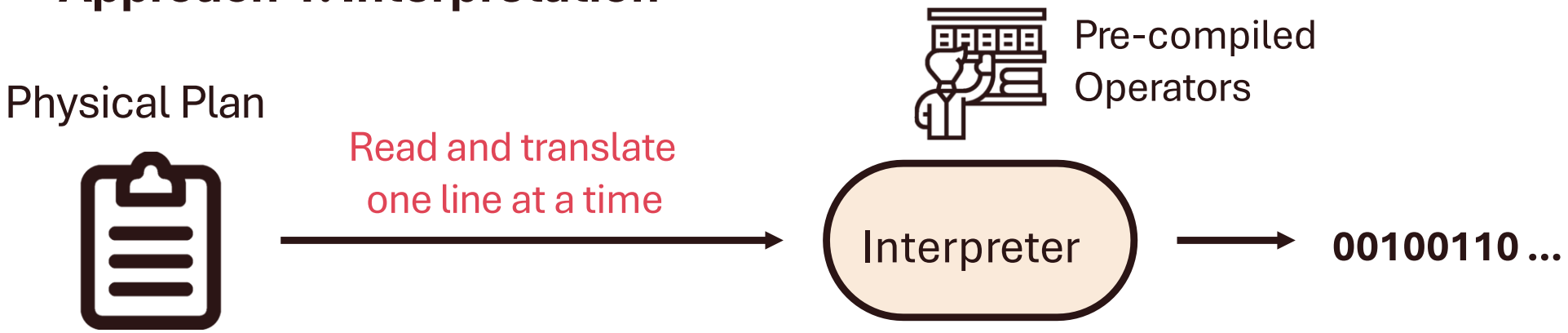
- Create, destroy, resize on demand
- Performance Isolation
  - Shared data, private compute
  - Typical usage pattern
    - Continuously-running VWs for repeating jobs
    - On-demand VWs for ad-hoc tasks
- Ephemeral worker processes
- **Columnar, Vectorized, Push-Based**

Execution engine design space

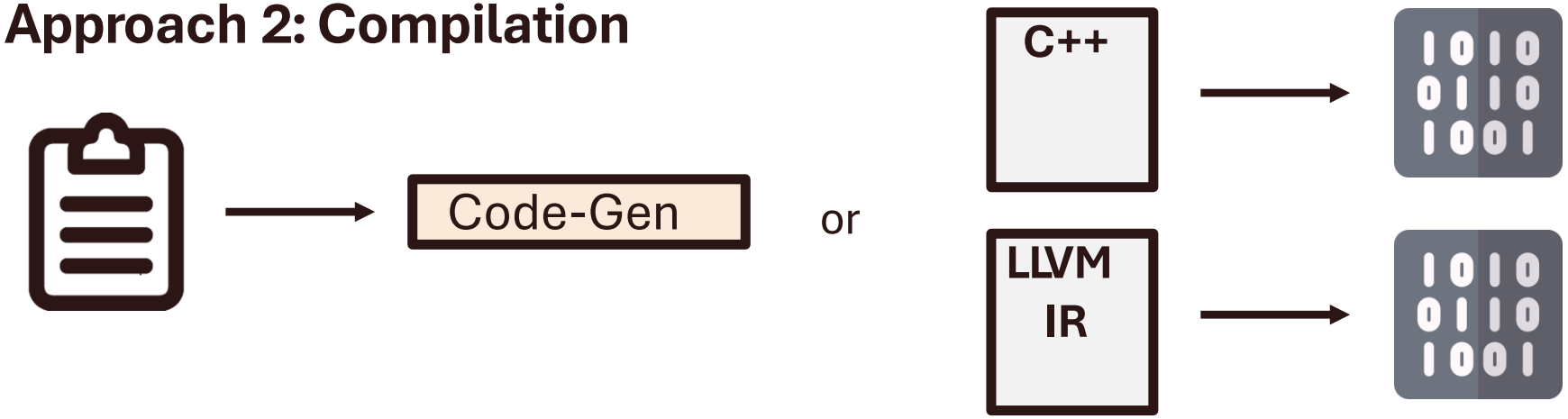
- **Engine Type**
  - Interpretation
  - Compilation (Code-Gen)
- **Execution Model**
  - Iterator / Volcano
  - Fully-Materialized
  - Vectorization
- **Pipeline Direction**
  - Pull
  - Push

Executing the plan

- **Approach 1: Interpretation**

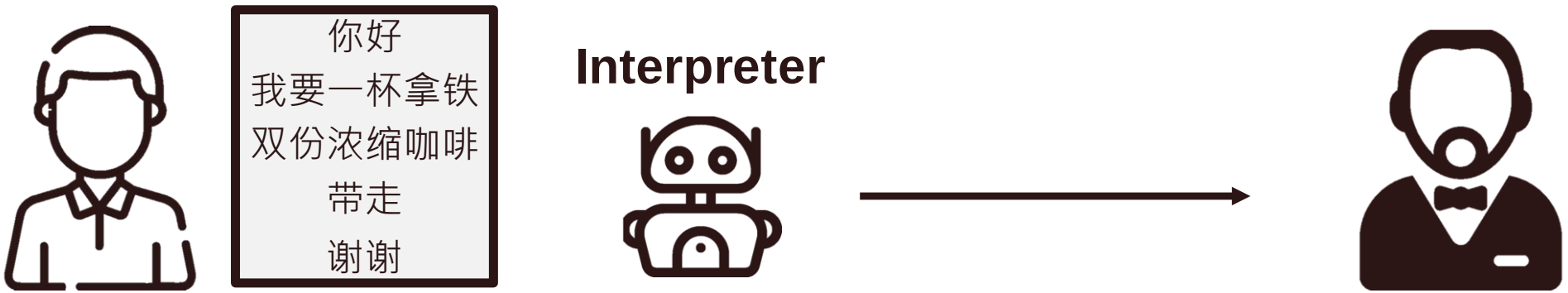


- **Approach 2: Compilation**



Aside: interpreting vs. compiling

- **Complier**: bring the pre-translated sheet



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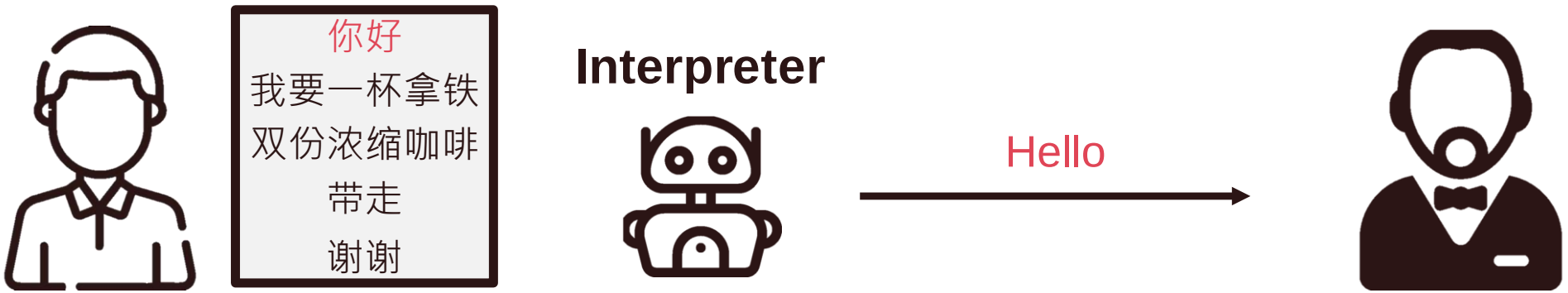

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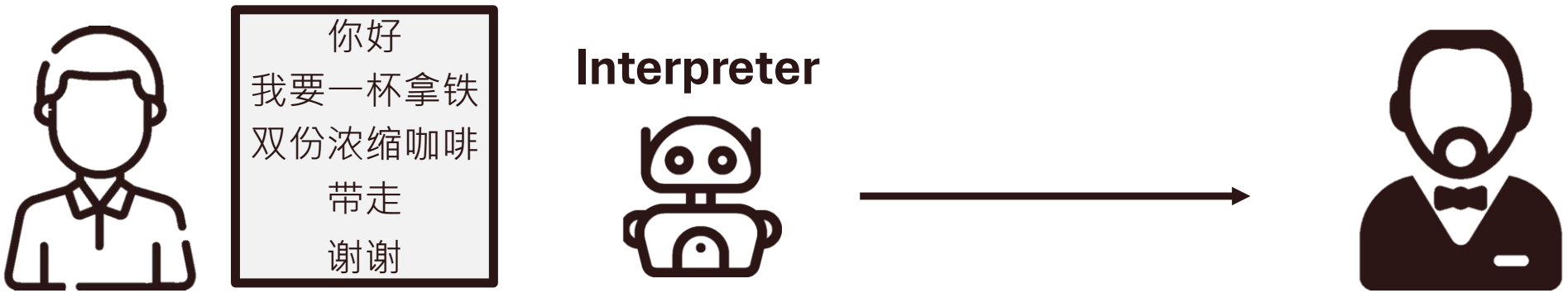

Pros

- No need for code analysis beforehand
- Easier to test and debug
- Cross-platform

Cons

- Need interpreters
- Execution is often slower

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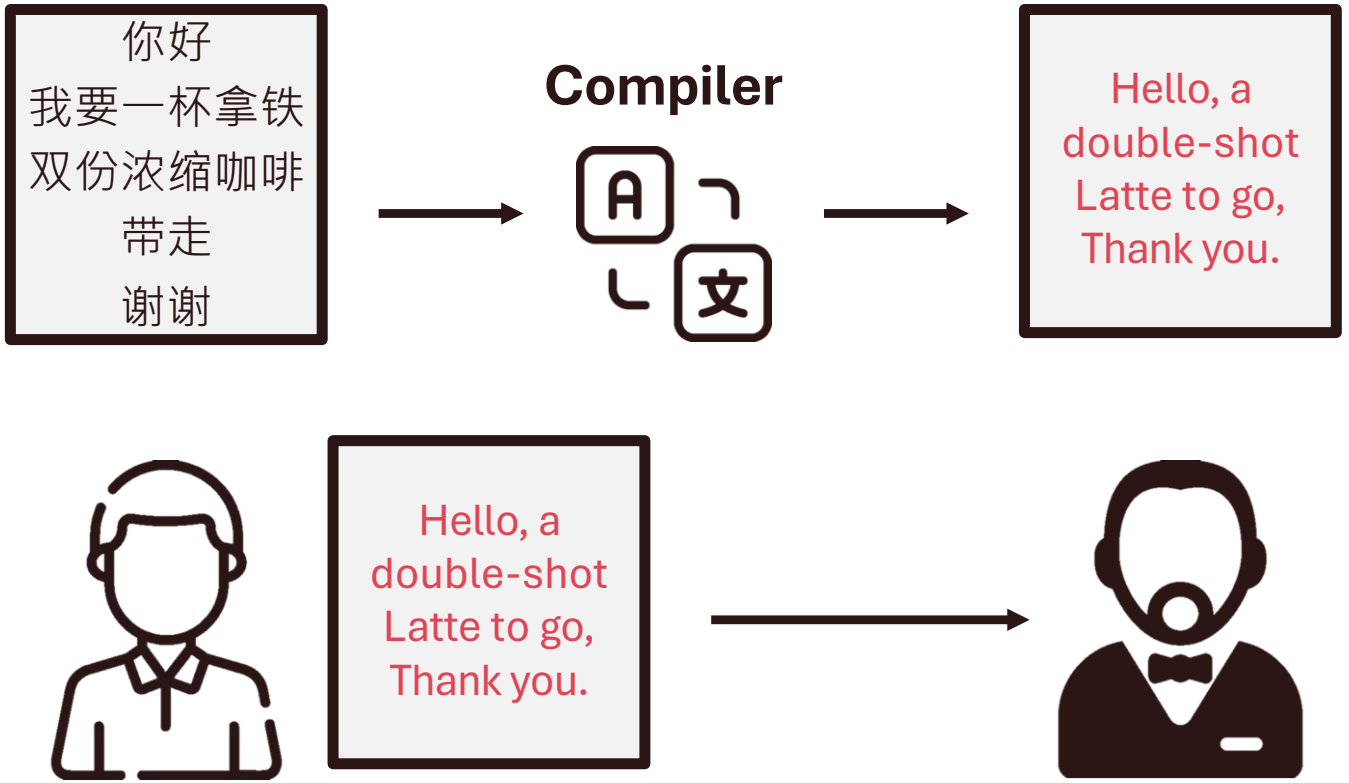


Pros

- Faster, ready-to-run
- Code better optimized

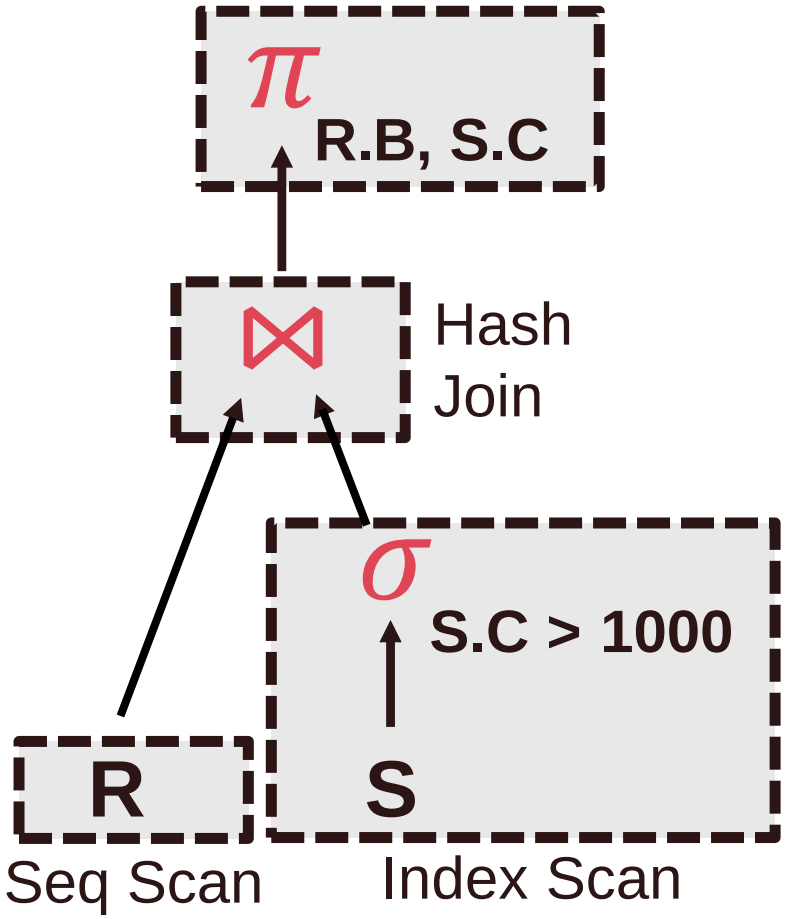
Cons

- Long extra compile time
- Requires more memory
- Hard to get it right
- Worse portability

Execution engine design space

- **Engine Type**
  - **Interpretation**
  - Compilation (Code-Gen)
- **Execution Model**
  - Iterator / Volcano
  - Fully-Materialized
  - **Vectorization**
- **Pipeline Direction**
  - Pull
  - **Push**

Iterator/volcano model



- Each operator implements Next()
  - Emits an output tuple or NULL
- The root operator implements a **loop** that keeps invoking **Next()** on its child
- Execution can be **pipelined**
- Could have **pipeline breakers**
  - E.g., join, order by
- Elegant implementation

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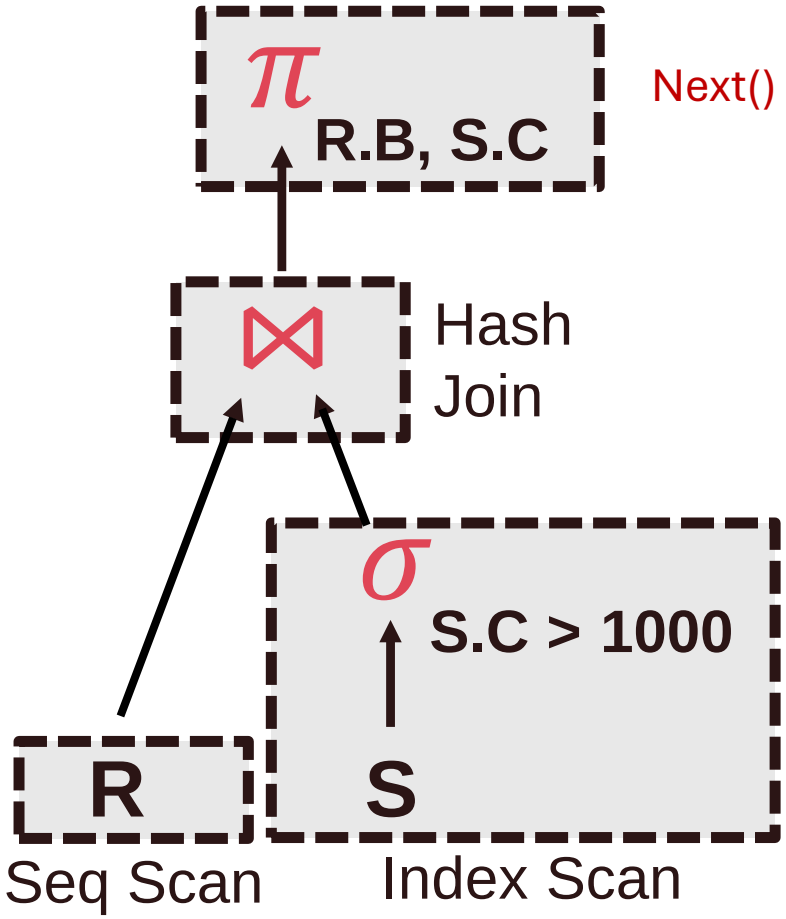

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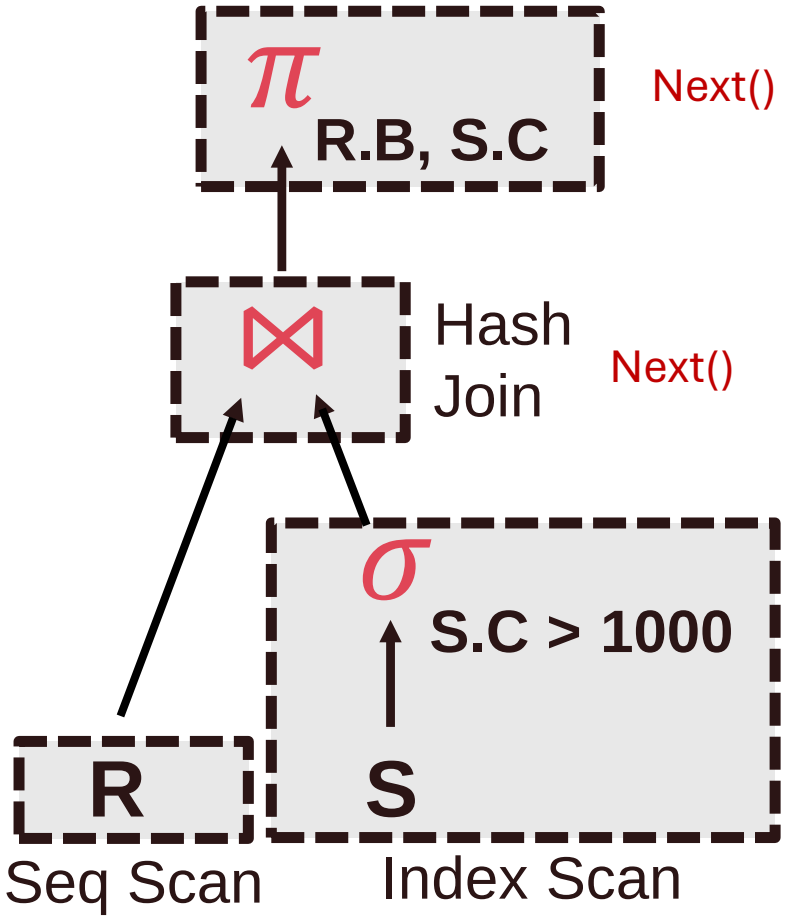

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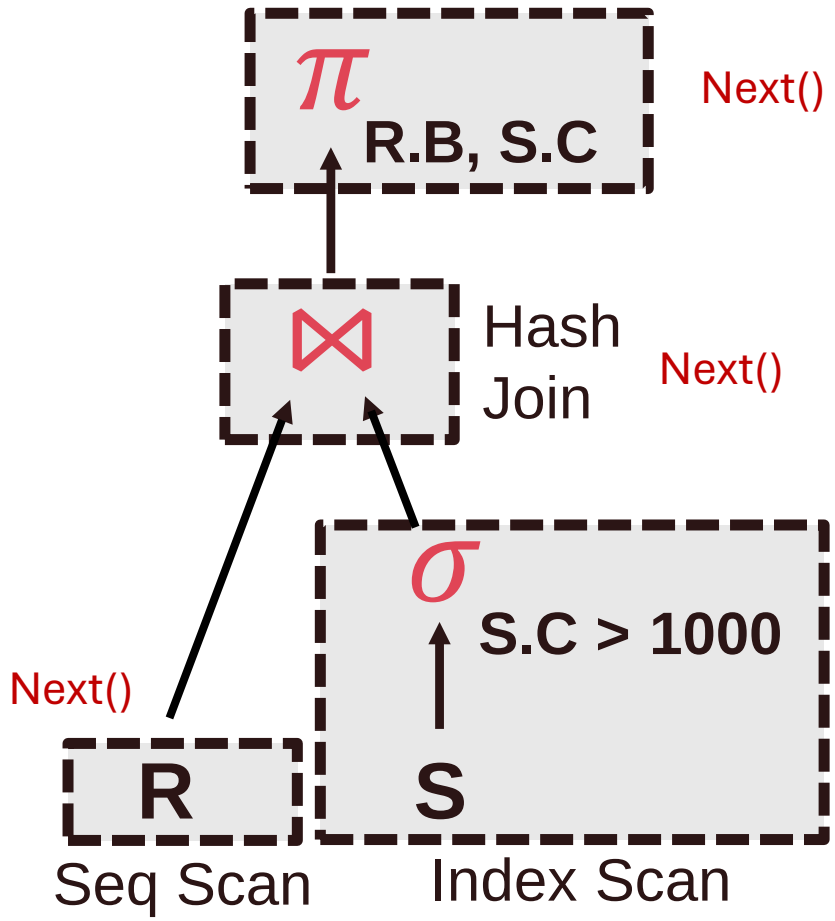

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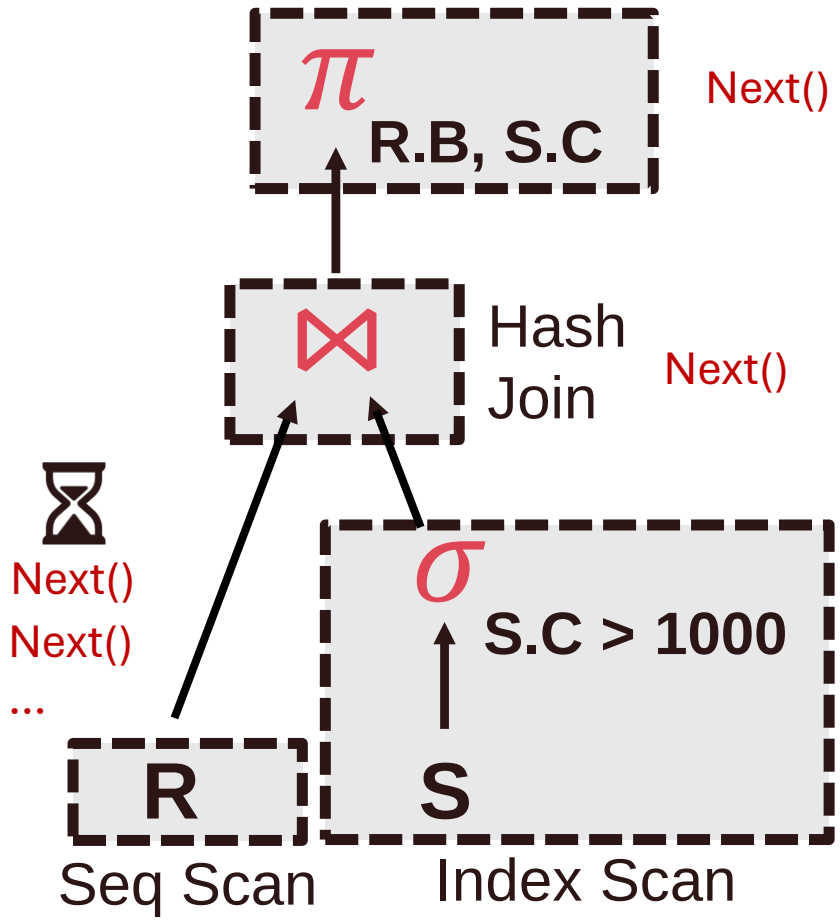

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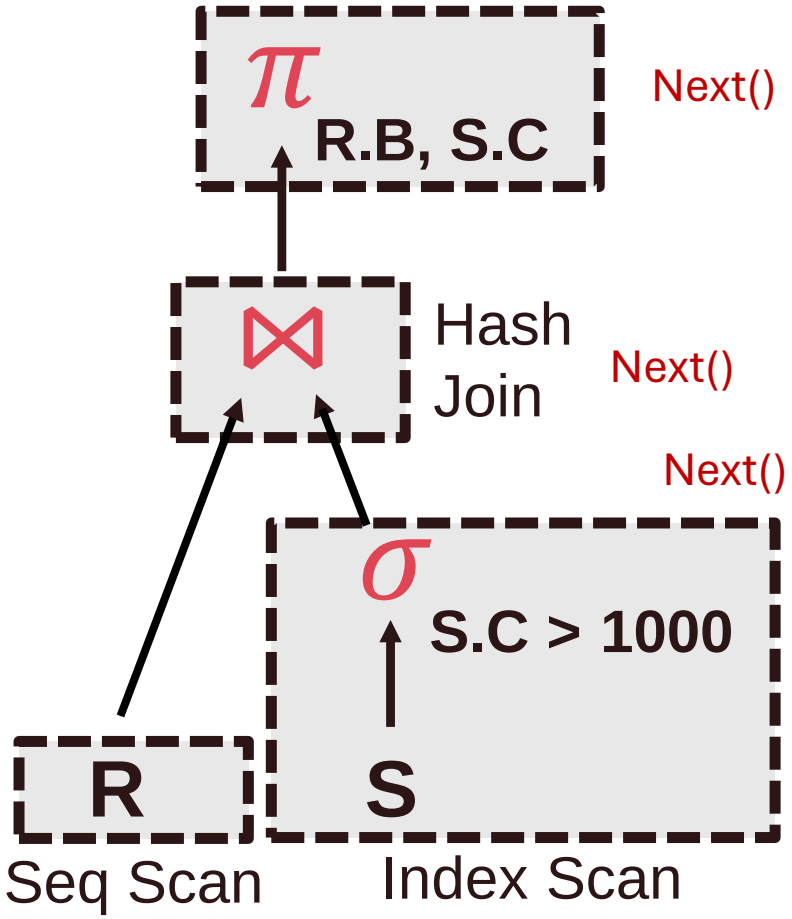

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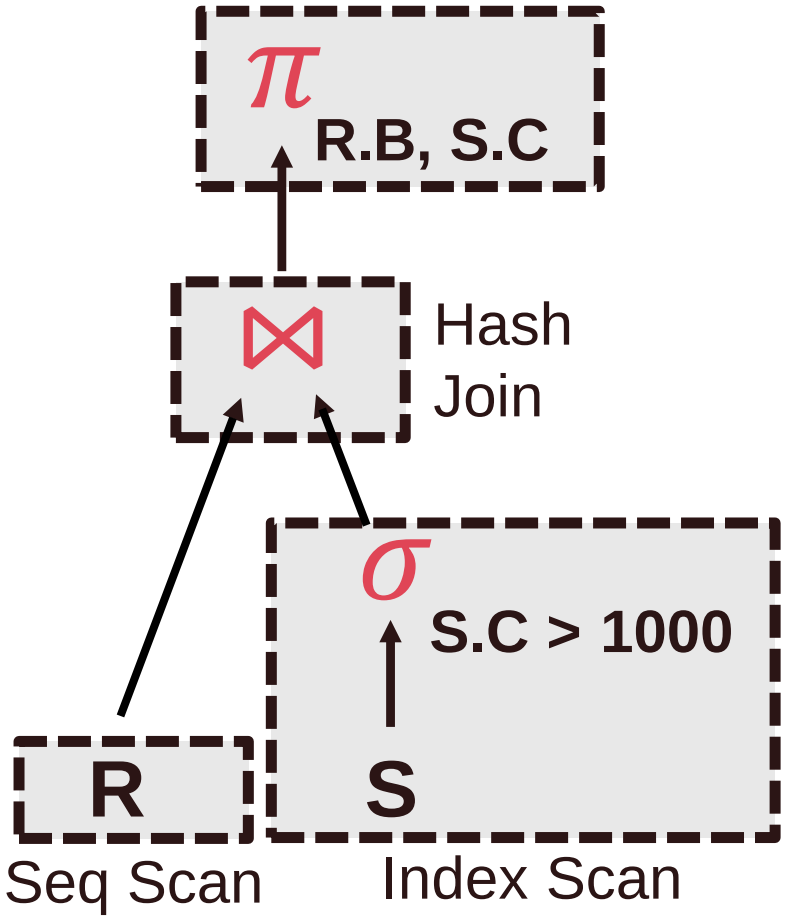
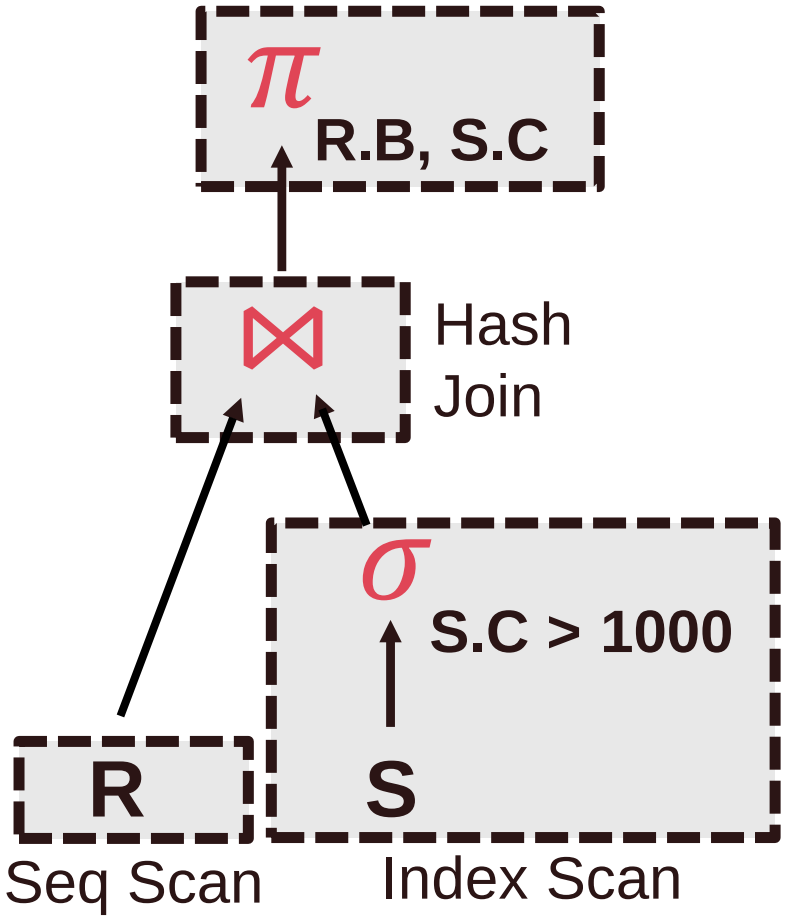



```
class AbstractExecutor {
    virtual void Init() = 0;
    virtual Tuple* Next() = 0;
protected:
    Context *ctx;
};
```

- Every operator implements the same interface
- Operators may have internal states

Fully-materialized model



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- Parent operator does not start until its children finish
- Non-pipelined

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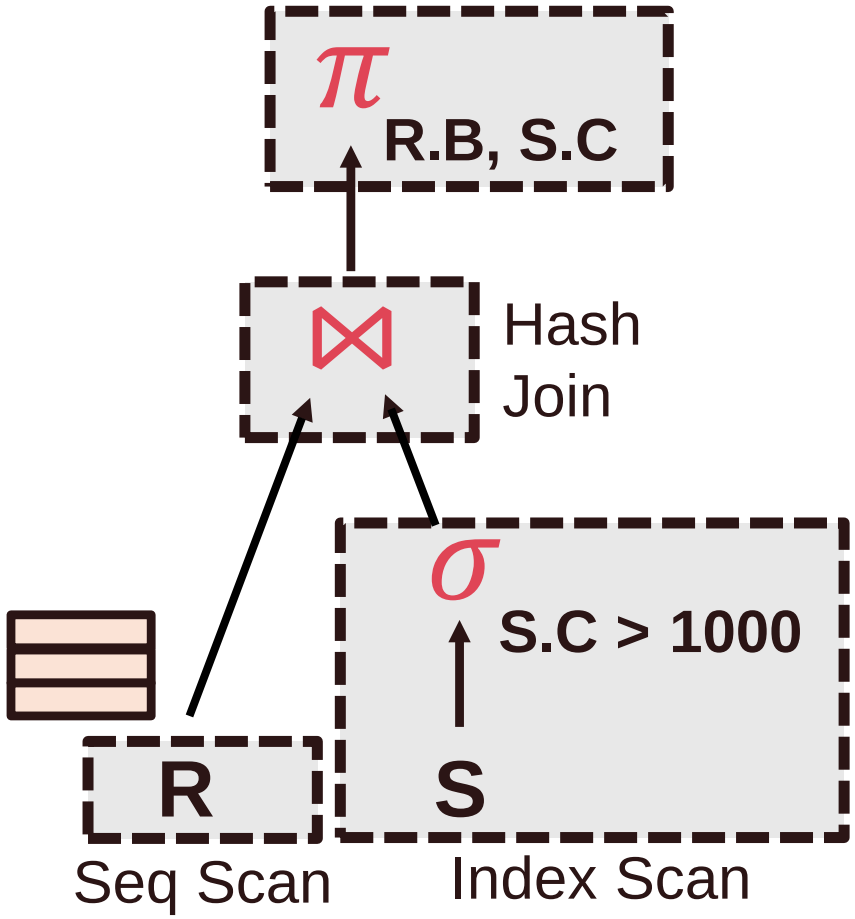

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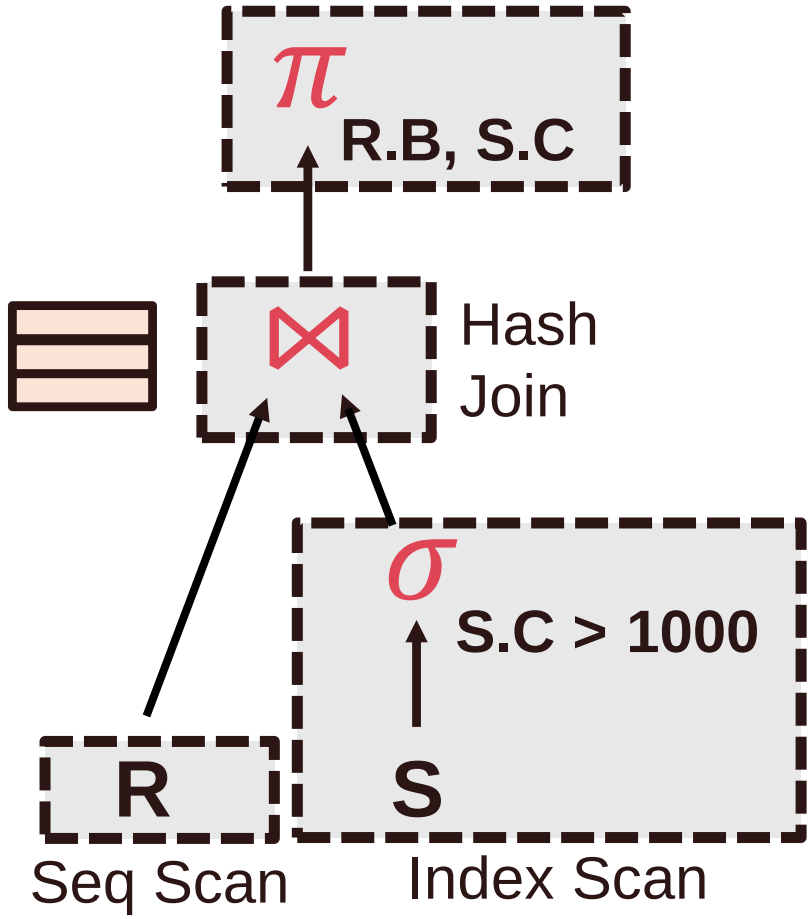

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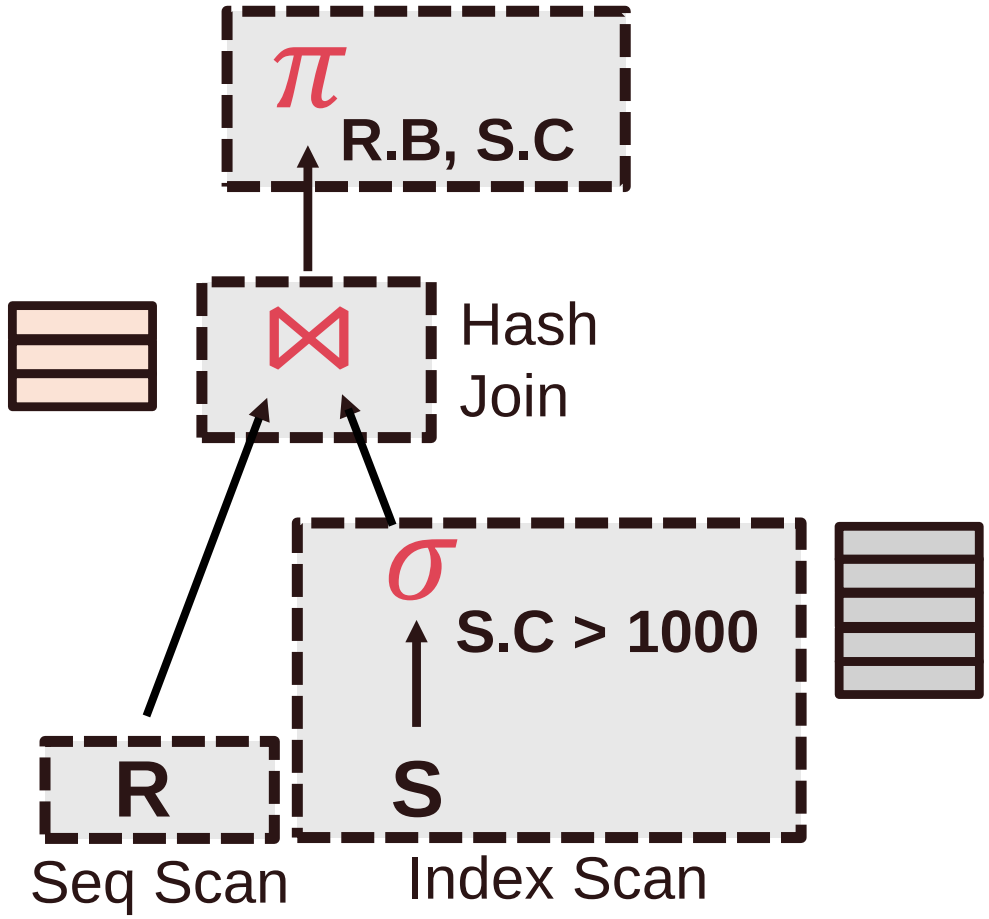

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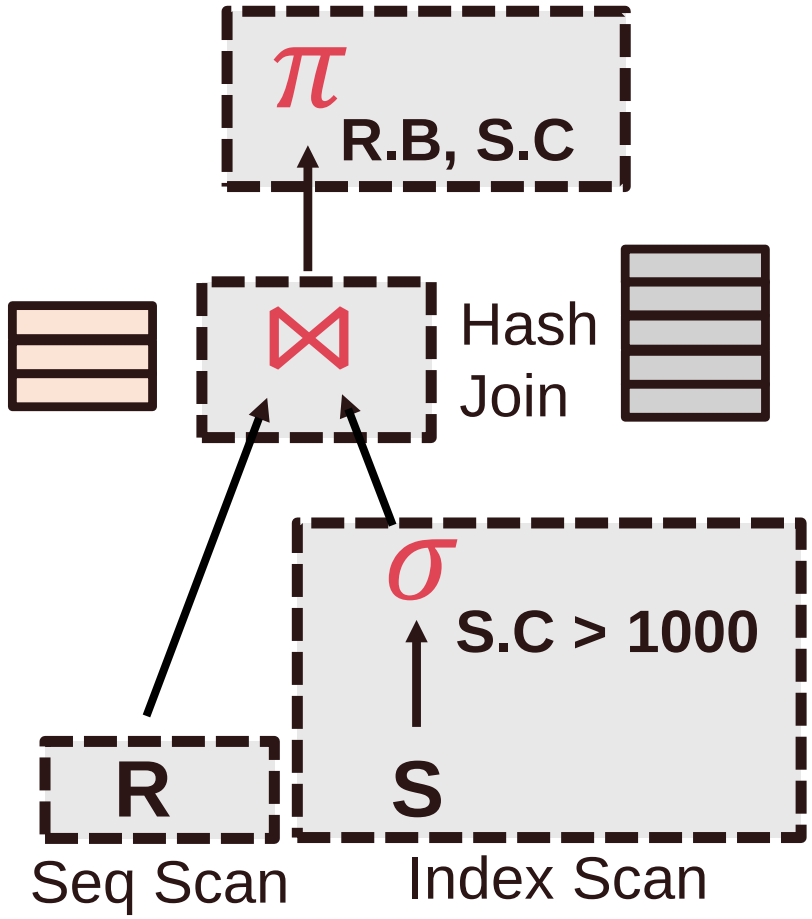

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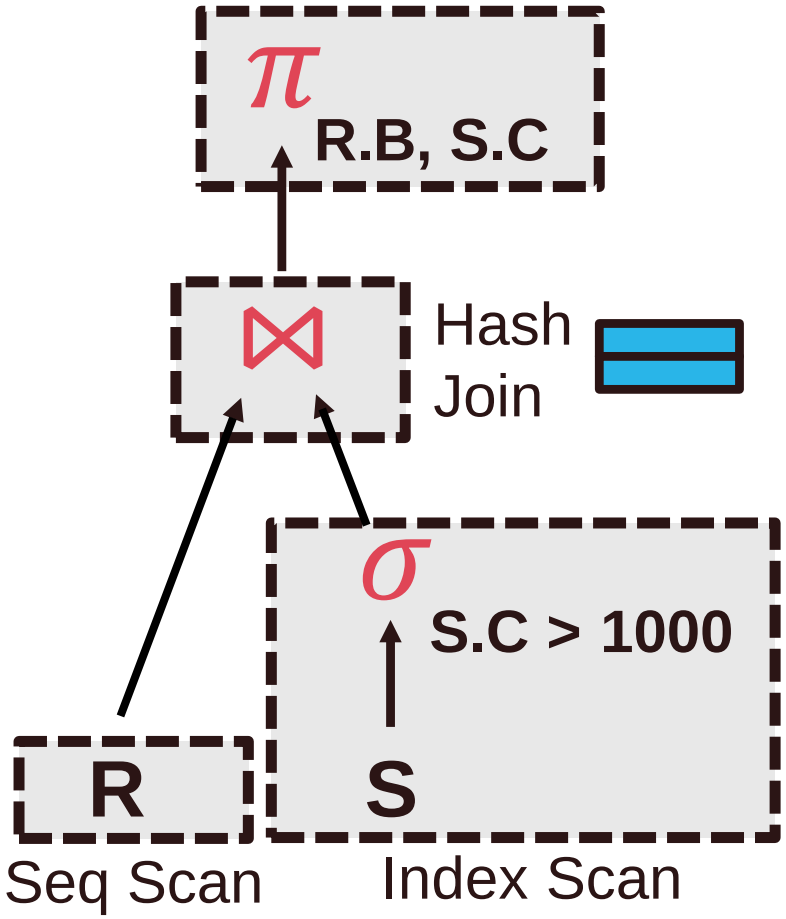

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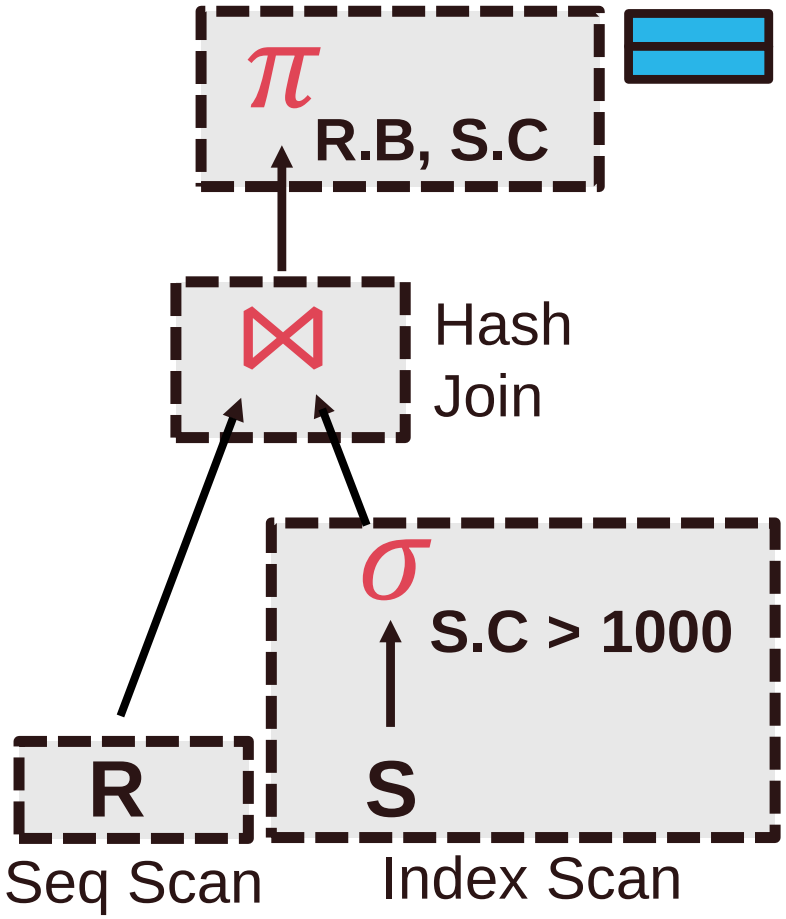

- Each operator stores its output in a single buffer and returns all at once
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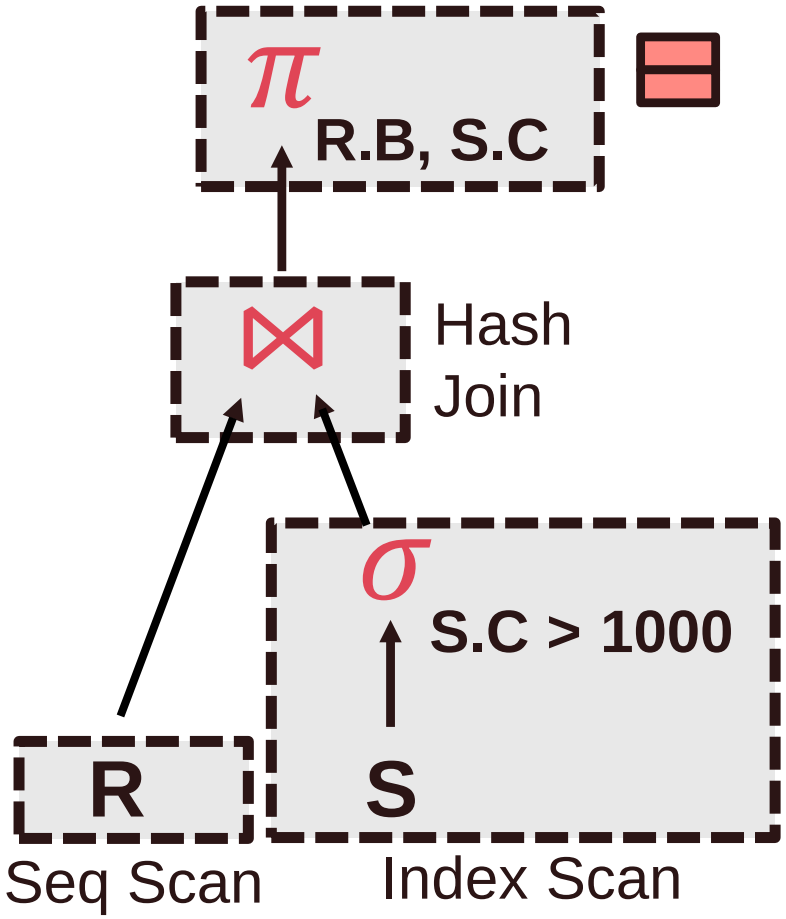

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Iterator vs. fully-materialized

Iterator / Volcano	**Fully-Materialized**
Tuple at a time	Operator at a time
Small intermediate results	Need extra memory for intermediate results
A lot of virtual function calls	Fewer function calls
Can benefit from pipelining	Can benefit from batch processing (e.g, SIMD)
Adopted by almost every OLTP DBMS	A few DBMSs (e.g., monetDB, VoltDB)

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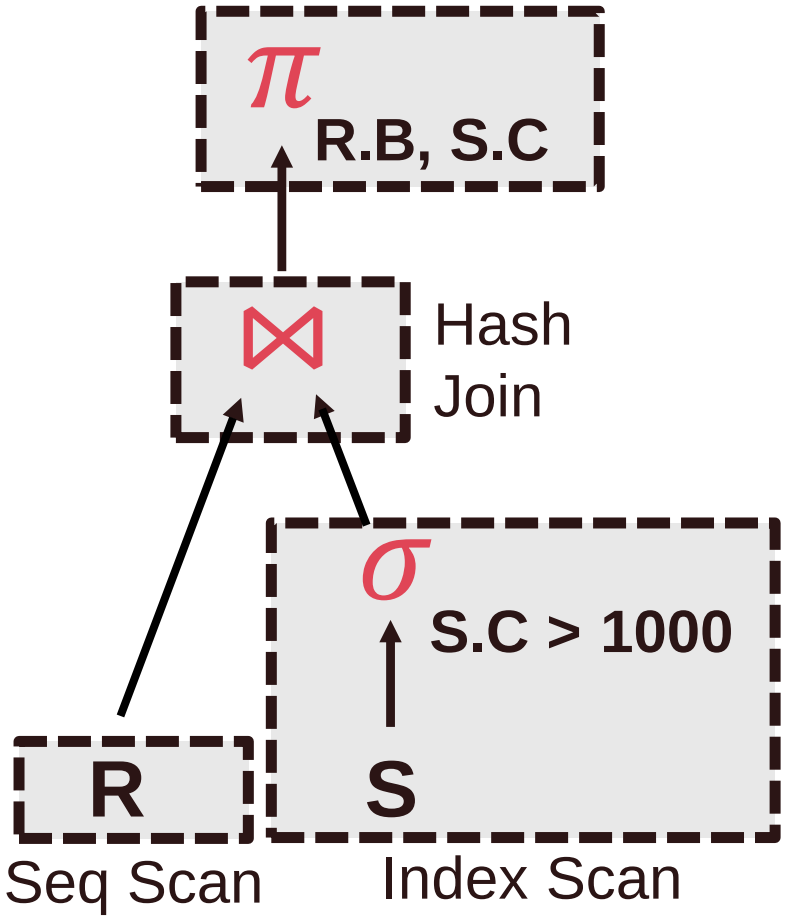
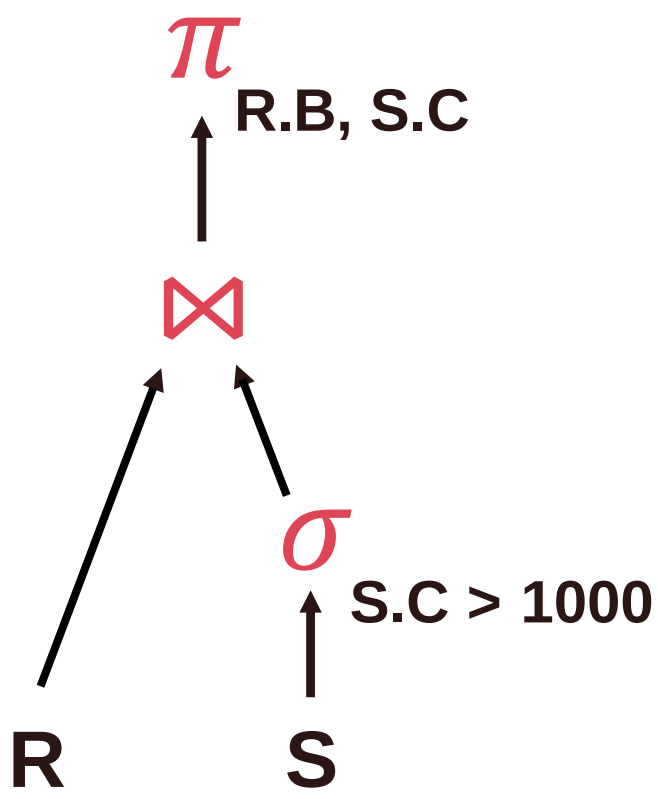
Vectorization model



- Every operator implements **NextBatch( )**
  - Emits a batch of tuples
- Can use SIMD instructions in operator's internal loop to accelerate processing
- Much fewer function calls compared to the iterator model
- Ideal for OLAP
  - Adopted by most interpreted OLAP engines today

Pipeline direction

- **Pull**
  - Parent operator “pulls” data up from its children
  - Via function calls such as Next( )
  - Most common way, easier to understand and implement
- **Push**
  - Child operator “pushes” data to its parent
  - Similar to producer-consumer model
  - Easier to “fuse” operations so that data stays in CPU register as long as possible



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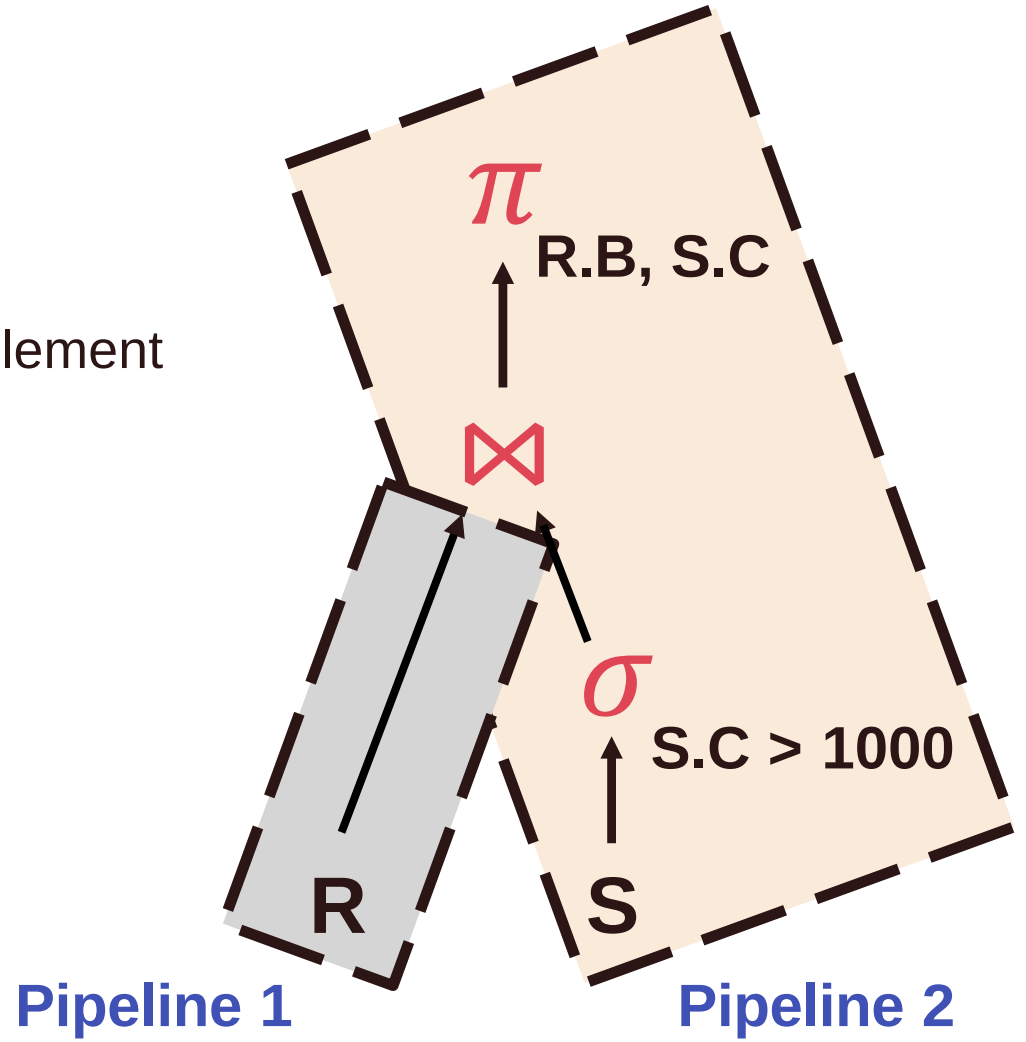
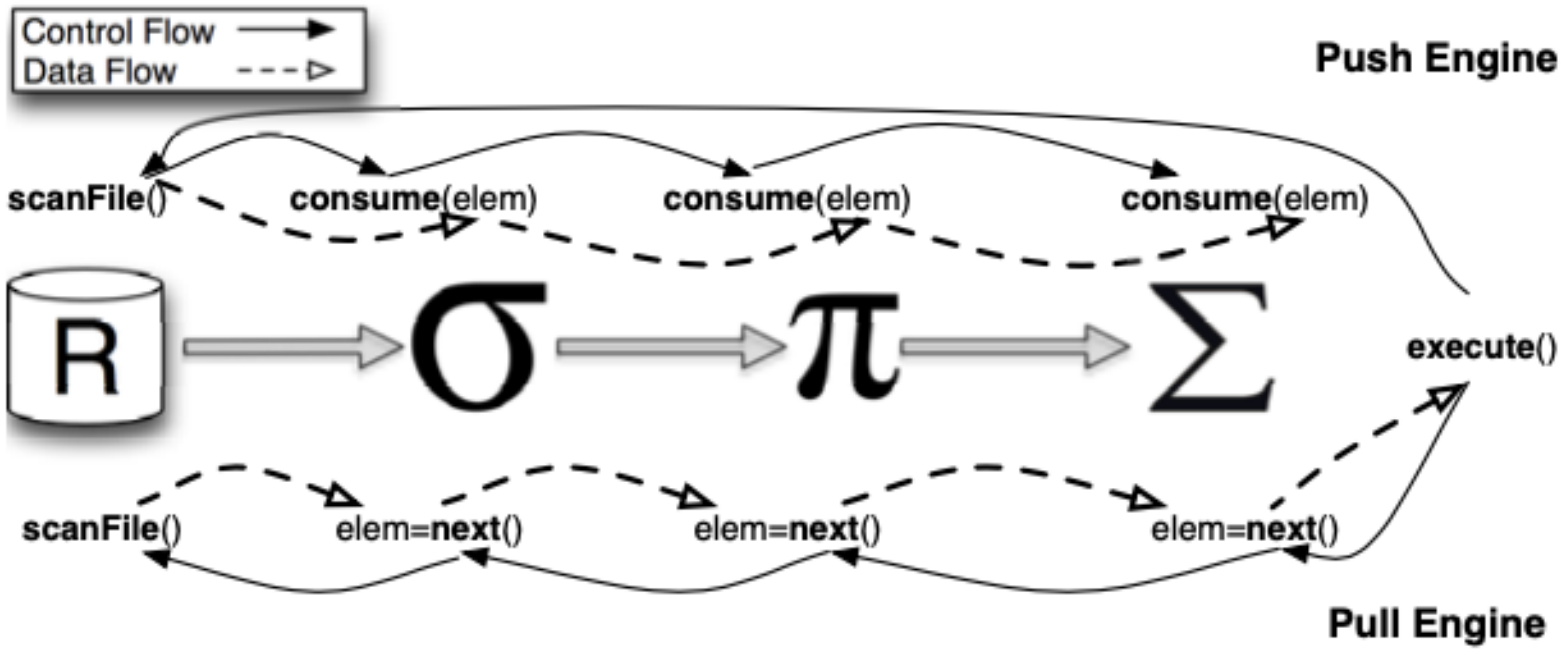
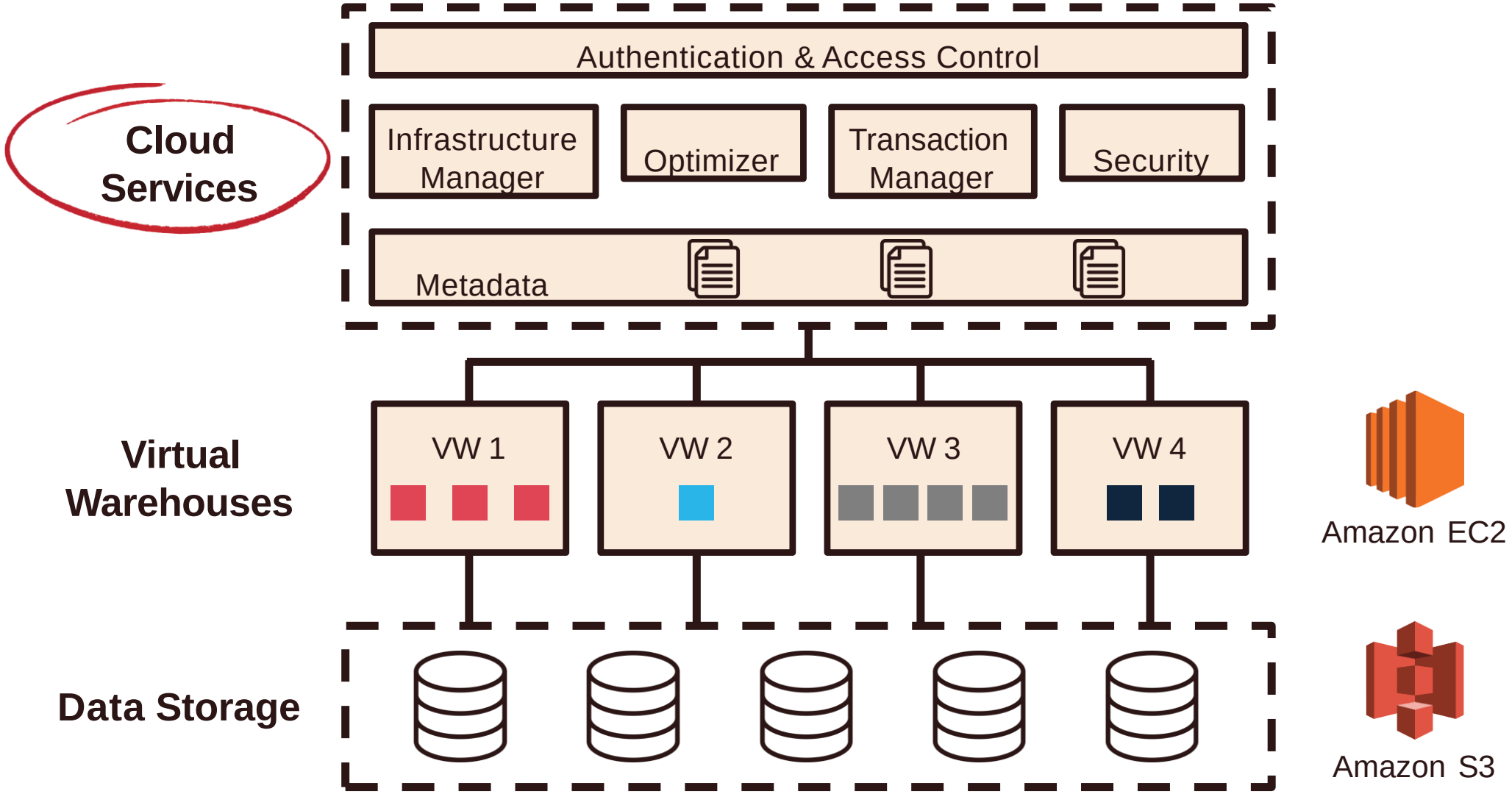


Pipeline direction

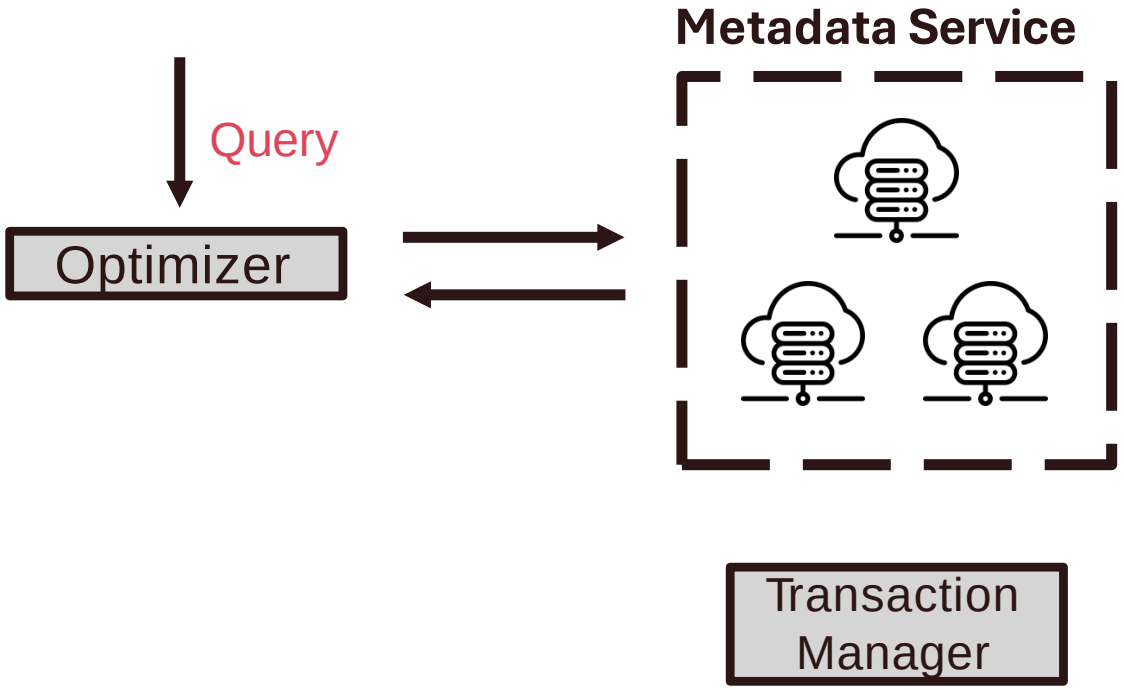



```
SELECT SUM(R.B)
FROM R
WHERE R.A < 10
```

Snowflake architecture



Cloud services: the brain



- **Optimizer**
  - Cascade-style
  - Scan set **pruning**

Pruning and re-clustering

How to avoid full table scan?

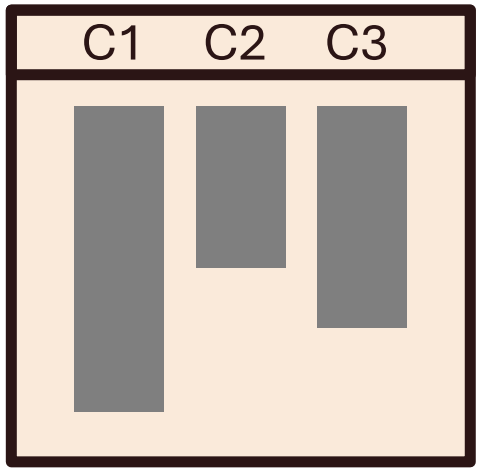
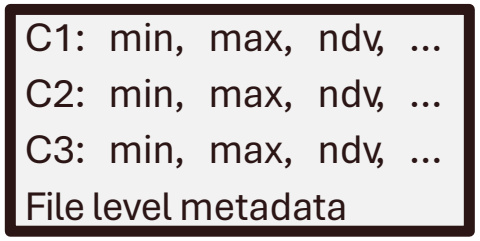


Table File

Pruning and re-clustering

How to avoid full table scan?

Zone Map



Cached in Metadata Service

Prune at compile and run time

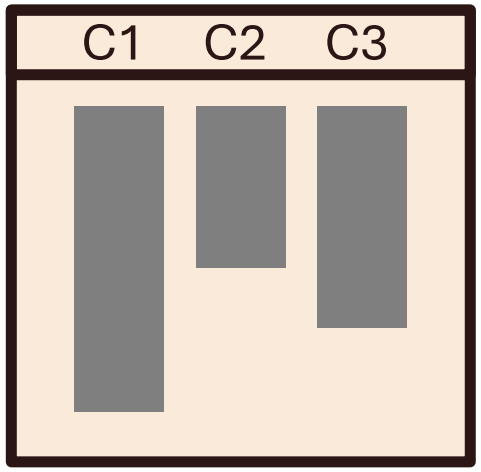


Table File

But it only works with data locality

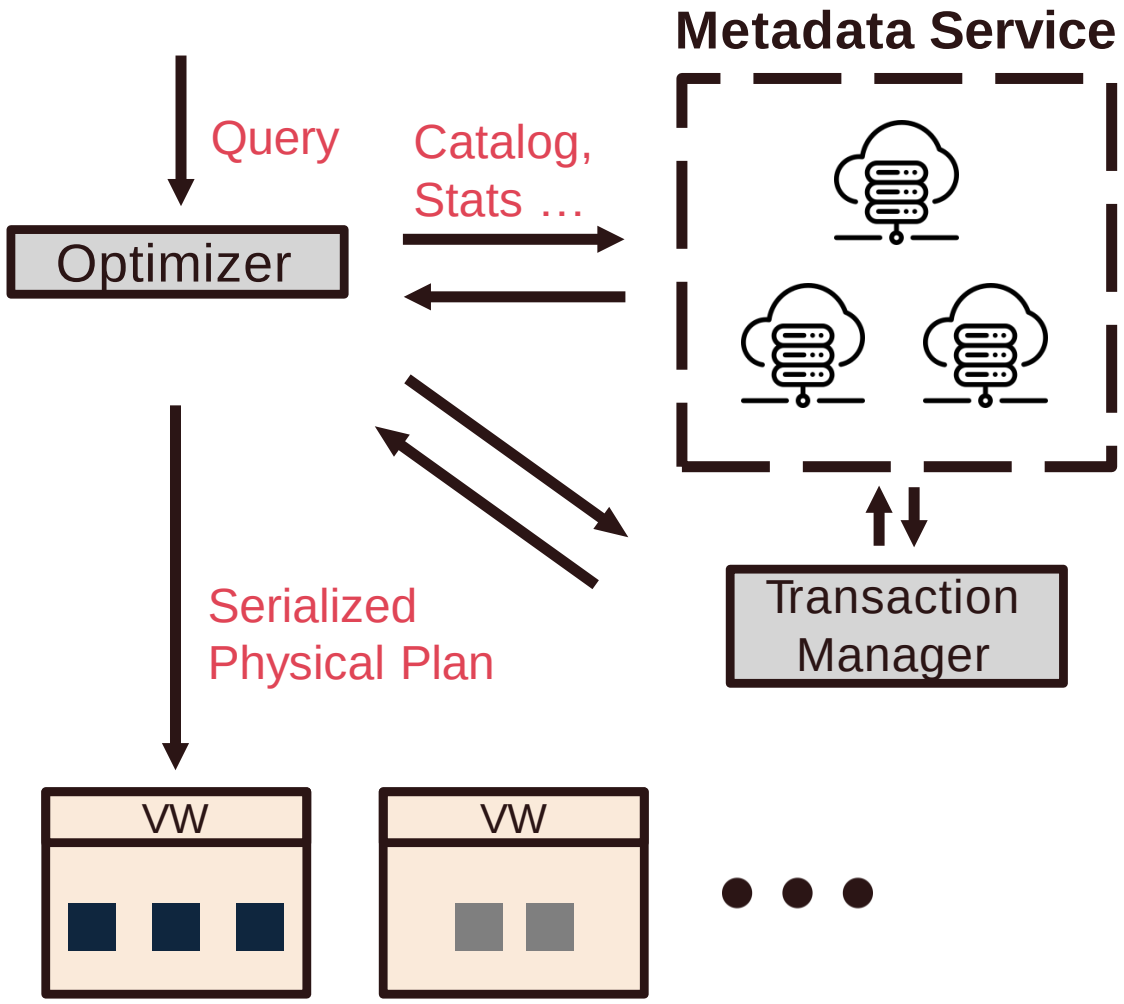
select count(*) from TBL where C1 > 'S'

Reclustering

Keep data "mostly" sorted

Automatic, incremental in the background

Cloud services: the brain



- **Optimizer**
  - Cascade-style
  - Scan set **pruning**
- **Metadata Service**
  - Stand-alone **FoundationDB** cluster for low latency accesses
  - Info needed for query compilation
    - Catalog, Stats
    - Lock status, version info
    - Zone maps
- **Multi-Version Concurrency Control (Snapshot Isolation)**

Snowflake architecture summary

- Disaggregated compute and storage
- Immutable hybrid columnar files in object storage
- Virtual warehouses provide elasticity and performance isolation
- Vectorized push-based execution engine
- Ephemeral storage system for caching intermediate results and persistent files
- Multi-tenant, always-on cloud services
- Separate fast metadata store
- Cascades-style optimizer, zone maps for scan pruning

Data lakes and warehouses: outline

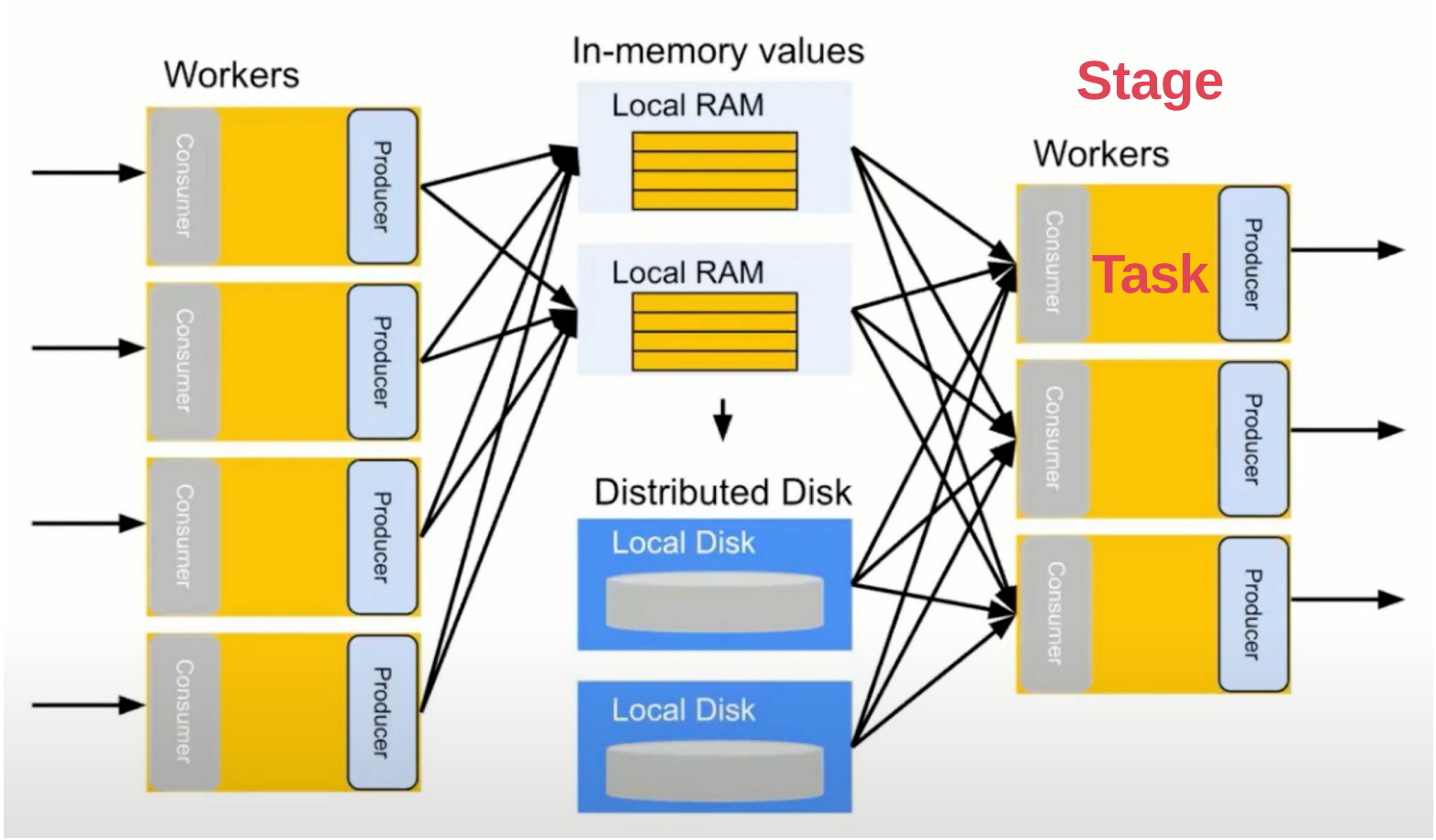
- Data lakes and warehouses
- Case studies
  - Snowflake
  - **Other offerings**

Google BigQuery

- Originated from the Google **Dremel** project
  - First database system with disaggregated compute and
  - storage In-situ data processing ⟶ **data lake**
  - Become commercial product BigQuery in 2012
- Serverless scalable analysis
  - On-demand pricing & capacity-based pricing
  - Columnar storage (Capacitor) similar to Parquet & ORC
  - Vectorized engine
  - **In-memory shuffle service**

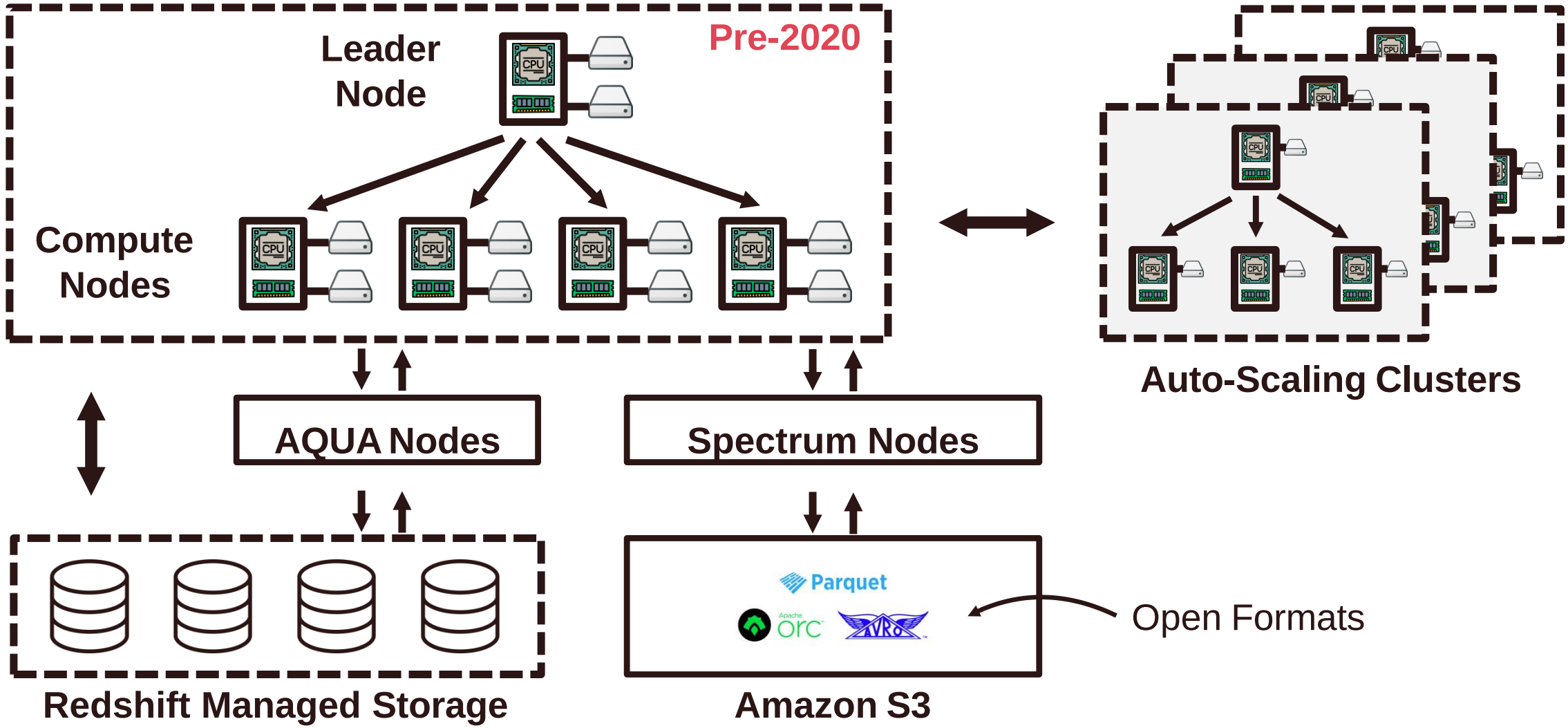
In-memory shuffle service

Google BigQuery



- Fault-Tolerance
- Straggler Avoidance
- Dynamic Resource Allocation
- Performance Overhead

Amazon Redshift



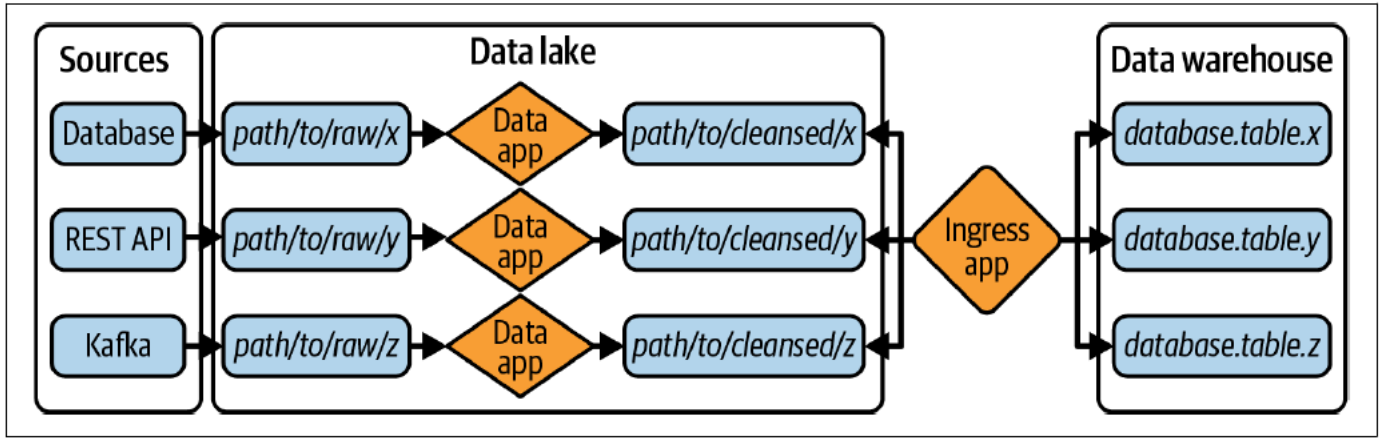
Amazon Redshift features

- Code-Gen (C++) plan fragments
- Compilation Service
  - Compiled-plan cache with 99.95% hit ratio
- Performance Optimizations
  - Min-max pruning
  - SIMD scan from local
  - SSDs AZ64 encoding

…

The dual-tier data architecture

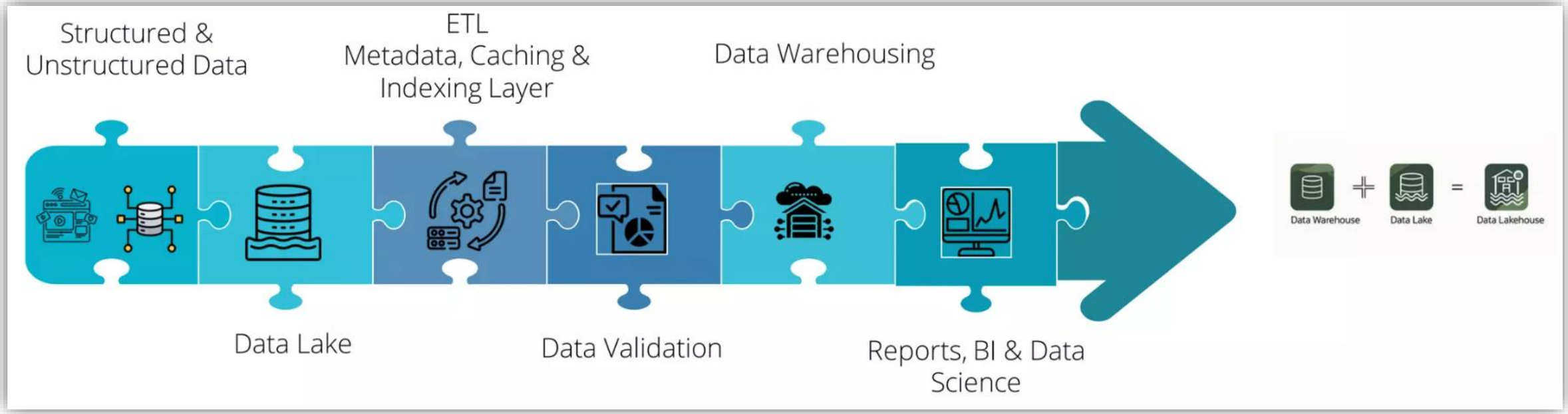
- Repository for storing large amounts of structured, semi-structured, and unstructured data without having to define a schema or ingest the data into proprietary internal formats.
    - Extract operational data from siloed data sources for writing into landing zones (/raw).
    - Read, clean, and transform the data from /raw and write the changes to /cleansed.
    - Read from /cleansed (could do additional joining and normalization) before writing out the warehouse.



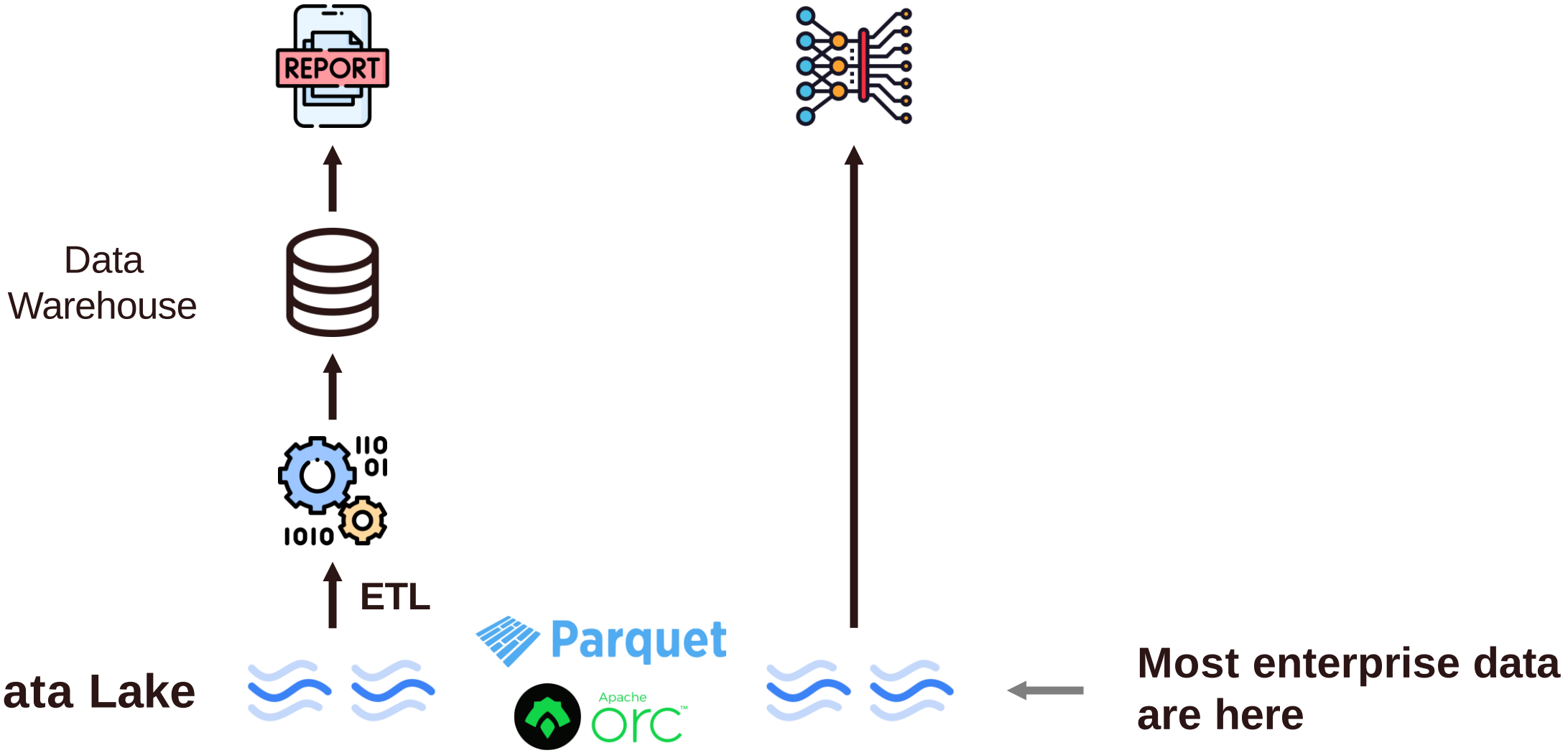
- Complex staging, redundant storage and less efficient

Lakehouse

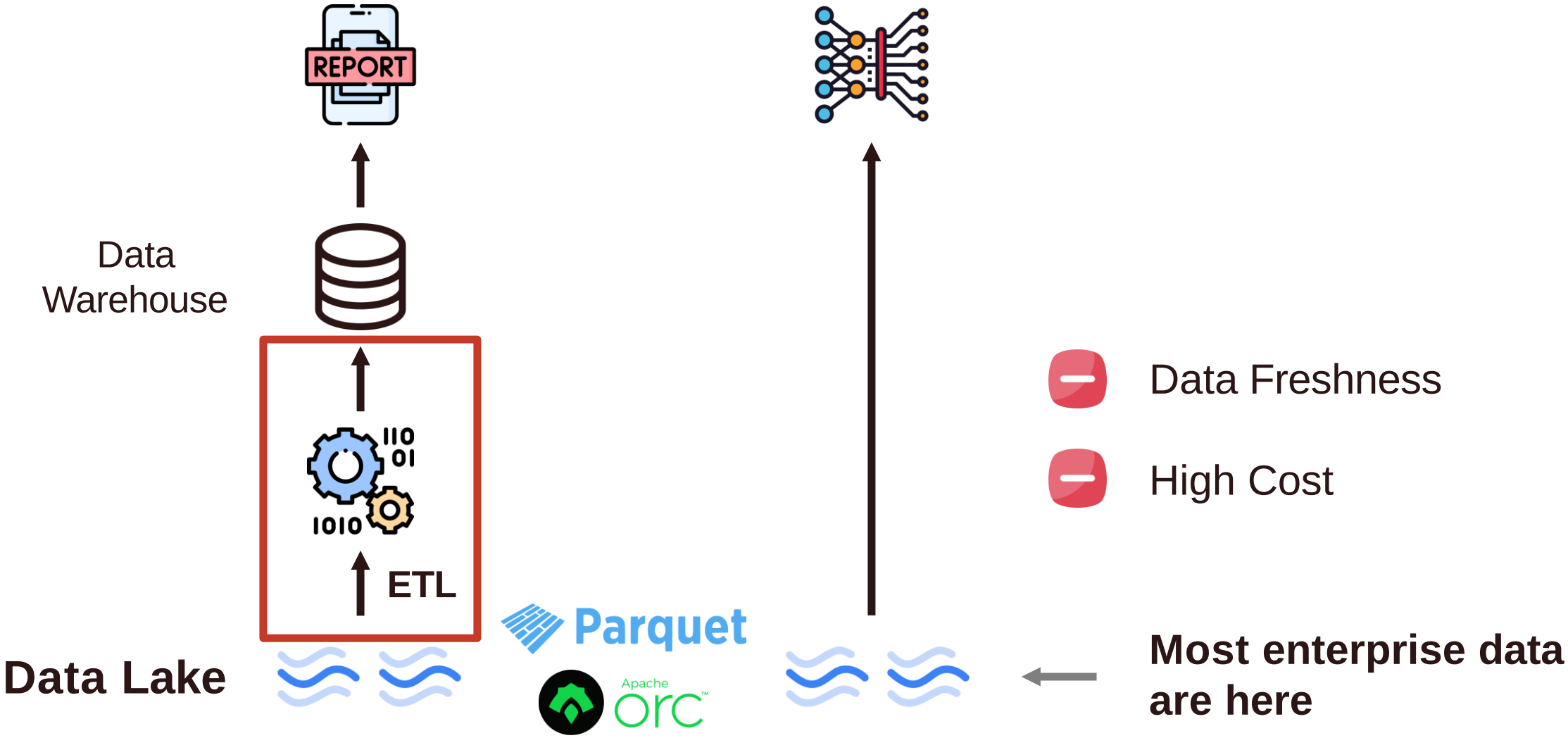
- A combination of data warehouse and data lake for better flexibility, low cost, and ACID transactions.
  - No need to copy data to data lake and warehouse separately.
  - Saves cost of infrastructure and staff.
  - Scalability and resilience.



Lakehouse


REPORT
Data Warehouse
ETL
Data Lake
Parquet
Apache orc
Most enterprise data are here

Lakehouse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Data Freshness
High Cost
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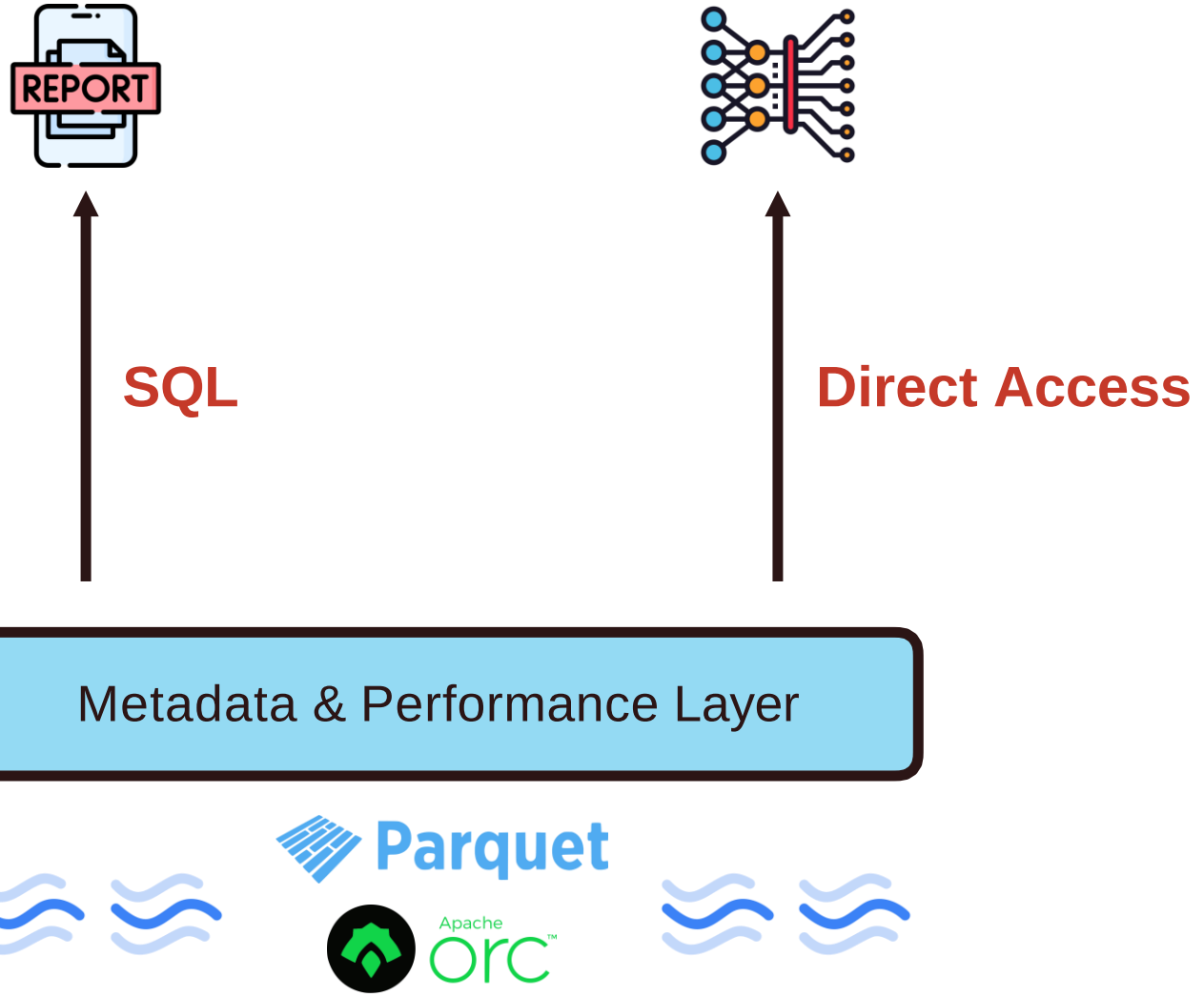
Lakehouse

databricks



Lakehouse performance optimization

- ➜ Zone-maps, indexes, … stored as Delta tables
- ➜ Caching hot data in SSD or DRAM
- ➜ New vectorized engine: **Photon**
  - Pull-based vectorized query processing
  - Precompiled operator primitives
  - Use position list rather than bitmap for late materialization

Delta Lake

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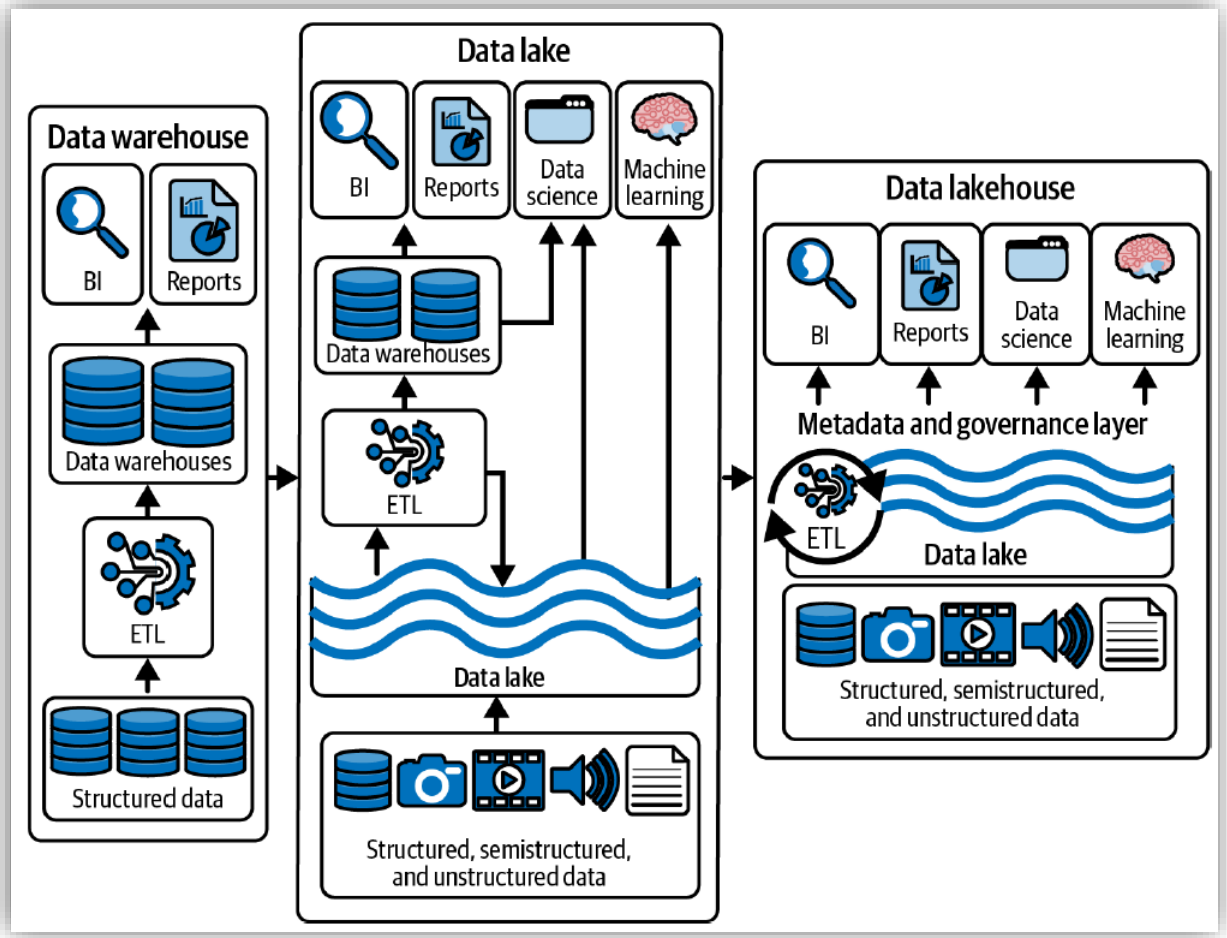
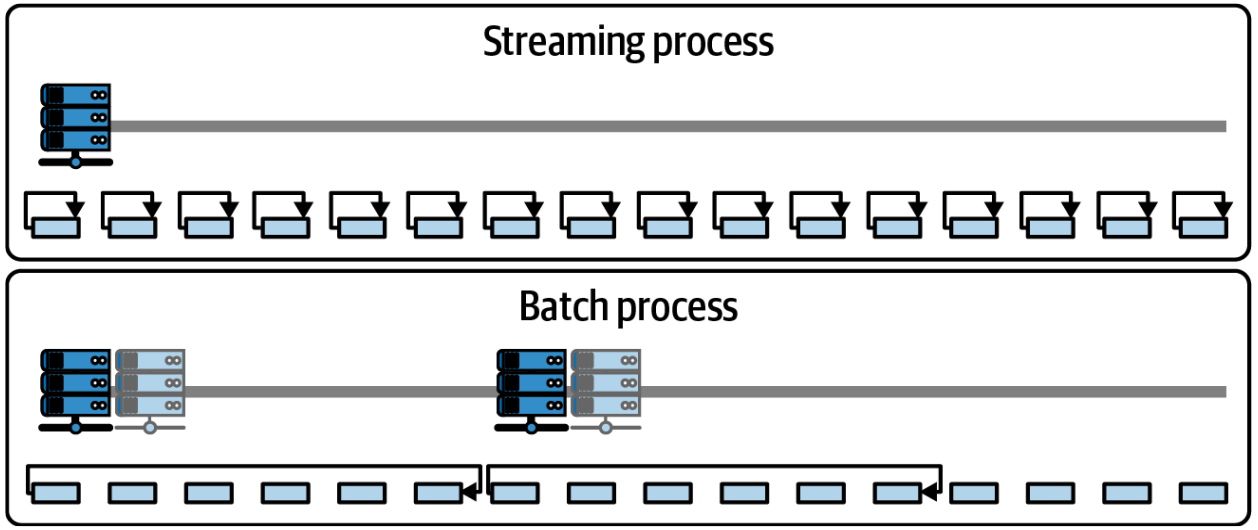


Streaming vs. batch processing

- **Streaming processing**: continuously processes data streaming, enabling instant insights and actions.
- **Batch processing**: deals with large volumes of data in chunks at scheduled intervals.



Streaming processing optimizes for **latency**, while batch processing optimizes for **throughput**.

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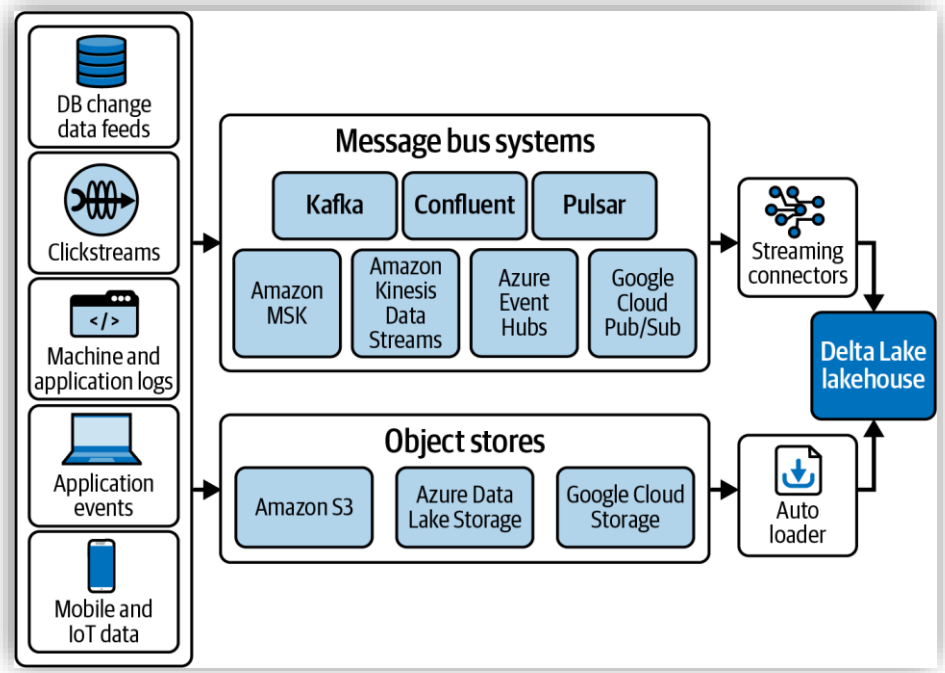
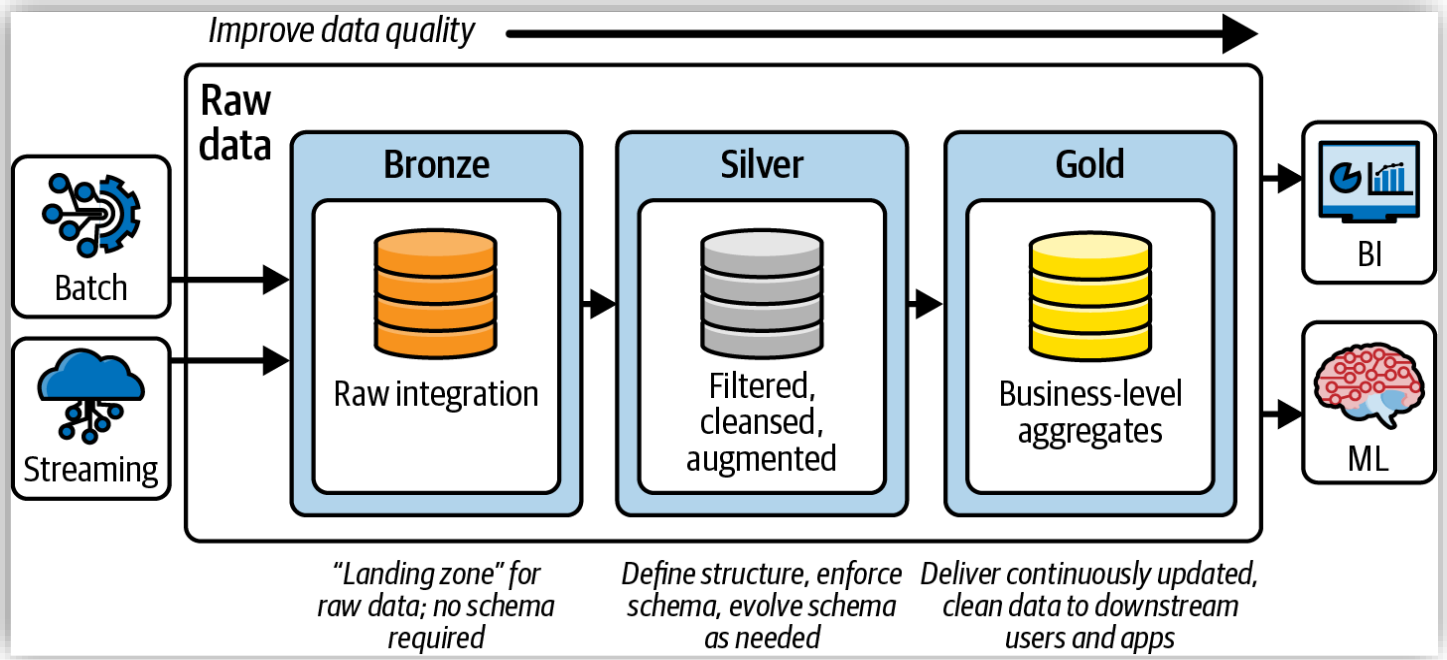


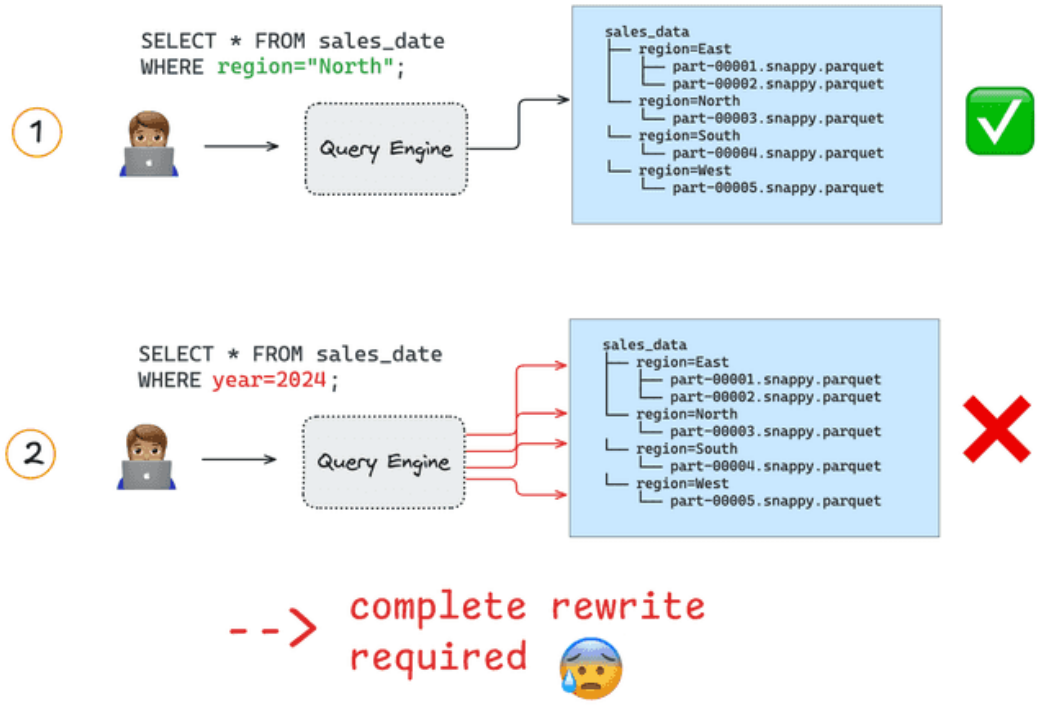
An example architecture diagram for stream processing applications with a Delta Lake sink from Databricks.

Medallion architecture

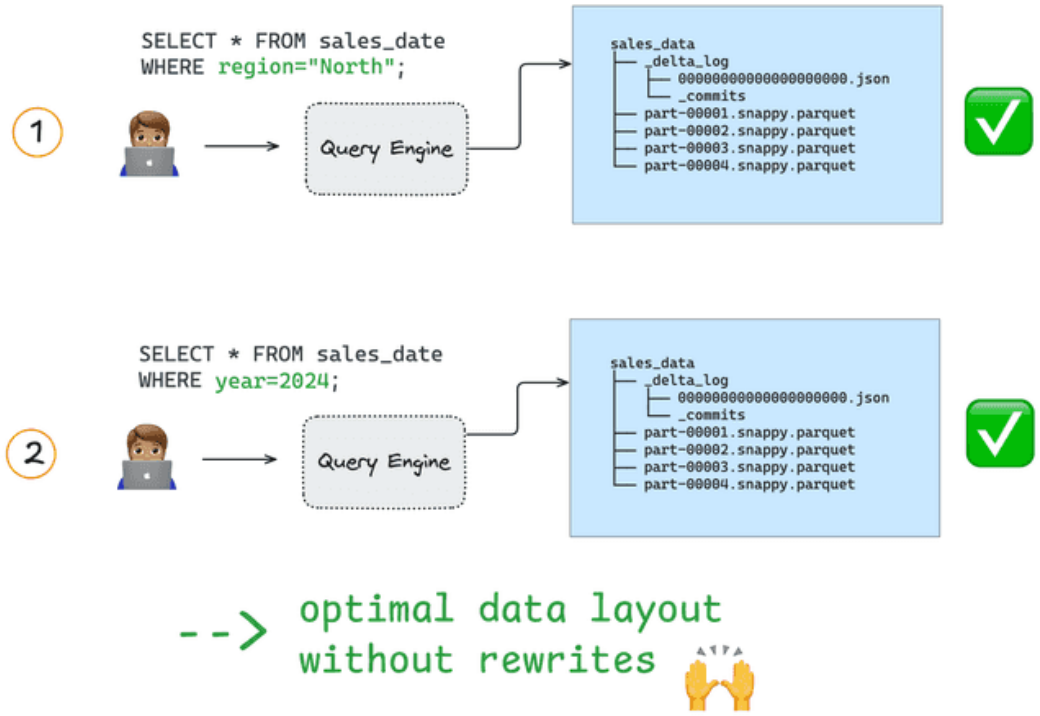
- A scheme to progressively refine datasets in the lakehouse.
  - Works for both batch or streaming sources.
  - Bronze: as simple as possible. E.g., Json parsing.
  - Silver: more complex preprocessing. E.g., text extraction from HTMLs.
  - Gold: complex joins and aggregates, w/ external data.



Liquid clustering



Hive-style partitioning on a partitioning column.



Liquid clustering automatically picks partitioning columns based on query patterns.

https://delta.io/blog/liquid-clustering/

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Credits and references

- Denny Lee et al. Delta Lake: The Definitive Guide.
- Andy Pavlo, CMU
- Dixin Tang, UT Austin
- Huanchen Zhang, Tsinghua