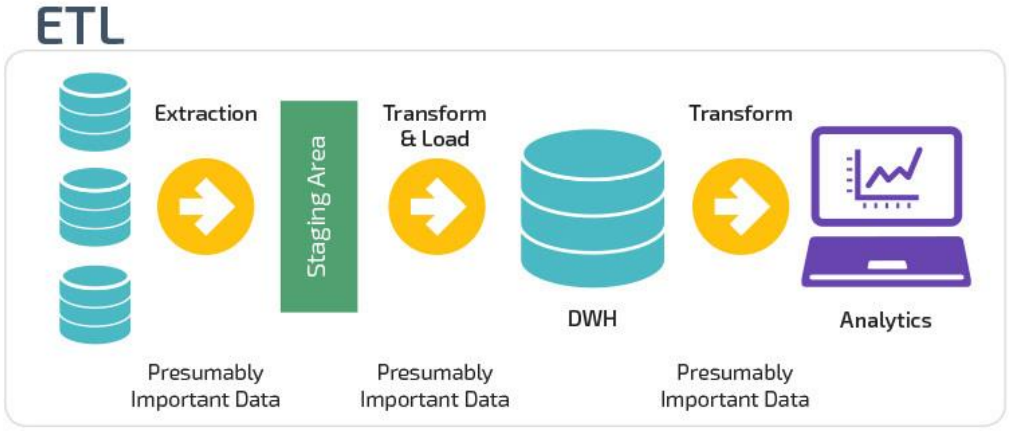
Cloud-Based Data Processing

OLAP in the cloud

Jana Giceva

Traditional OLAP / data warehouses

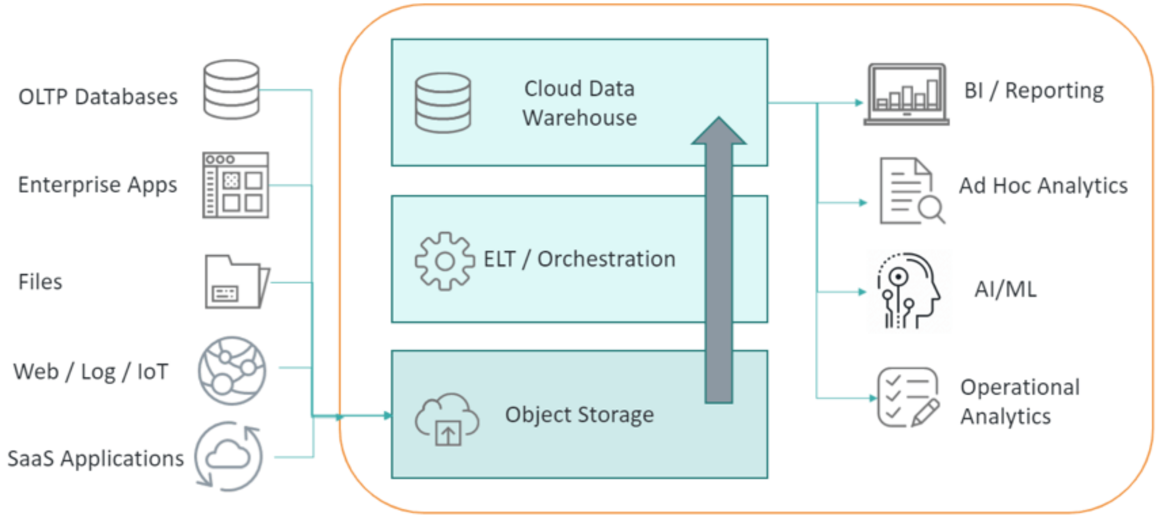
- Traditional data warehousing systems are built for:
  - Predictable, slow-evolving internal data
  - *Relational* data, structured in a *star*- or *snowflake* schema
  - Complex *ETL* (extract-transform-load) pipelines and physical tuning (compression, layout, etc.)
  - Limited number of users and use-cases


ETL
Extraction
Staging Area
Transform & Load
Transform
DWH
Analytics
Presumably Important Data
Presumably Important Data
Presumably Important Data

img src: https://panoply.io/data-warehouse-guide

Cloud-based data

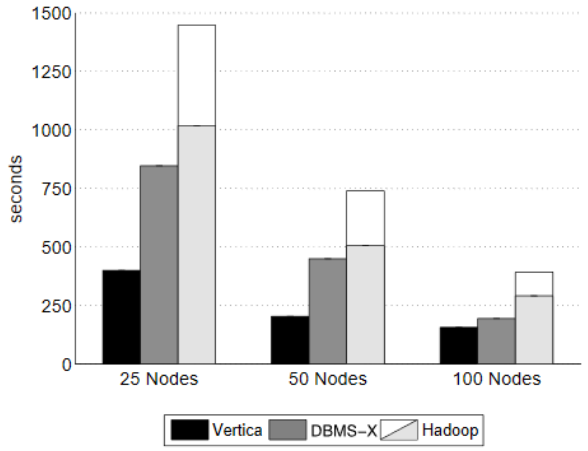
- **Data in the cloud:**
  - **Dynamic, external sources**: web, logs, mobile devices, sensor data, etc.
  - **ELT** (extract-load-transform) **instead of ETL – data transformation is done inside the system**
  - Often in **semi-structured data format** (e.g., JSON, XML, Avro)
  - Access required by many users, with very different use-cases



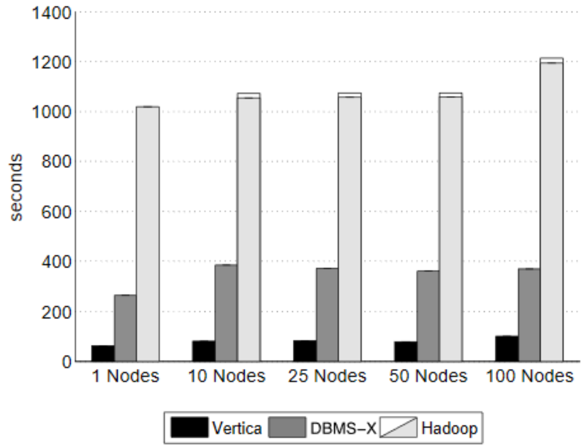
img src: InterWorks

Are DW still relevant in the era of BigData?

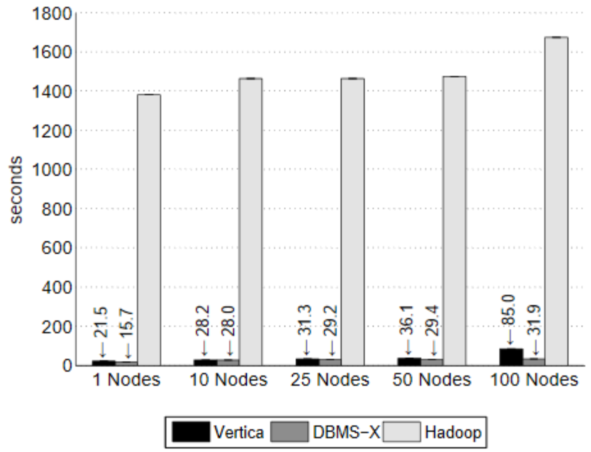
```
SELECT * FROM Data WHERE
field LIKE '%XYZ%';
```



```
SELECT pageURL, pageRank
FROM Rankings WHERE
pageRank > X;
```



```
JOIN
```



- Schemas are a good idea (parsing text is slow)
- Auxiliary data structures help boost performance (value indexes, join indexes)
- Optimized algorithms and storage structures: layout, data formatting, order of execution, choice of algorithm

Source: Pavlo et al. (2009). A Comparison of Approaches to Large-Scale Data Analysis. SIGMOD

Data warehouse system architecture

- Architecture: **shared-nothing**

- Important **architectural dimensions** and methods
  - **Storage**:
    - Columnar storage, compression, data pruning
    - Table partitioning, distribution

  - **Query engine**:
    - Vectorized or JIT code-gen
    - Query optimization
    - Fine- and coarse-grained parallelism and multi-tenancy

  - **Cluster:**
    - (Meta-) data sharing
    - Resource allocation and management

Data warehouse storage

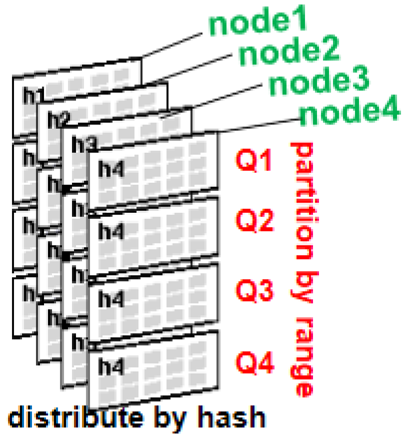
- **Data layout:** column-store vs. row-store
  - Column-stores only read relevant data (skip irrelevant data by skipping unrelated columns)
  - Suitable for analytical workloads (better use of CPU caches, SIMD registers, lightweight compression).
  - E.g., Parquet, ODC, etc.

- **Storage format**: compression is key!
  - Trades I/O for CPU and good fit for large datasets (storage) and I/O intensive workloads
  - Excellent synergy with column-stores
  - E.g., RLE, gzip, LZ4, etc.

- **Pruning:** skip irrelevant data using a MinMax index.
  - Data is usually ordered → can maintain a sparse MinMax index
  - Allows to skip irrelevant data horizontally (rows).

Table partitioning and distribution

- **Data is spread based on a key**
  - Functions: hash, range, list
- **Distribution** (system-driven)
  - Goal: parallelism
    - Give each compute node a piece of the data
    - Each query has work on every piece (keep everyone busy)
- **Partitioning** (user-specified)
  - Goal: data lifecycle management
    - Data warehouse e.g., keeps last six months
    - Every night: load one new day, drop the oldest partition
  - Goal: improve access pattern
    - When querying for May, drop P1,P3,P4 (partition pruning).

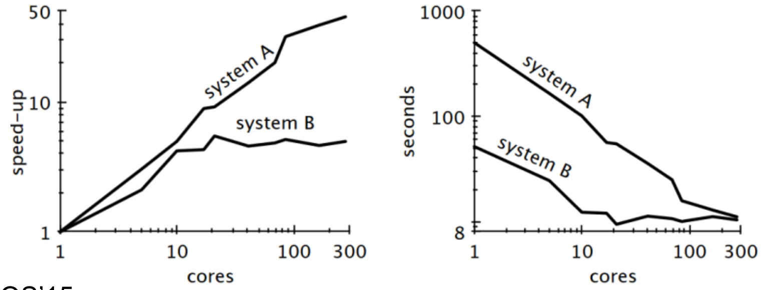


img src: P.Boncz (CWI)

Query Execution

Scalability is not as important unless you can make the most out of the underlying hardware.

Scalable system	Cores	Time [s]
Spark	128	857
Giraph	128	596
GraphX	128	419
SingleThreaded	1	275



Src: McSherry et al. Scalability! But at what COST? HotOS'15

- **Vectorized execution**
  - Data is pipelined in batches (of few thousand rows) to save I/O, and greatly improve cache efficiency.
  - E.g., Actian Vortex, Hive, Drill, Snowflake, MySQL's Heatwave accelerator, etc.

- And/or **JIT code generation**
  - Generate a program that executes the exact query plan, JIT compile it, and run on your data.
  - E.g., Tableau/HyPer/Umbra, SingleStore, AWS Redshift, etc.

Cloud-native warehouses

- Design considerations for scalability, elasticity, fault-tolerance, good performance.
  - **Should we keep compute and storage tightly coupled?**

- **Separate tiers**, **different challenges** at **cloud-scale** for cloud-data:
  - **Storage**:
    - Abstracting from the storage format
    - Distribution and partitioning of data even more relevant at cloud-scale
    - Data caching models across the (deep) storage hierarchy (cost/performance)
  - **Query execution**:
    - Distributed query execution: combine scale-out and scale-up
    - Global resource-aware scheduling
    - Distributed query optimization

- **Service form factor**
  - *Reserved-capacity* services vs. *serverless* instances

Data placement in the Cloud

- There is **no data locality**
  - To create elasticity, compute needs to be de-coupled from storage
  - i.e., AWS S3 files are always stored remotely
    - high latency (100-200ms) and slow bandwidth (20-125MB/s)

- **Distribution and partitioning is very common**
  - Distribution – allows jobs to be parallelized
  - Partitioning – data-pruning or data lifecycle management

- Some **locality** can be created **by caching**
  - Caching in memory (e.g., Spark)
  - Caching on local ephemeral disk (e.g., DBIO cache in Databricks, Vertica EON, etc.)
    - 0.03ms latency, ~500MB/S bandwidth, ~500GB size (per core)

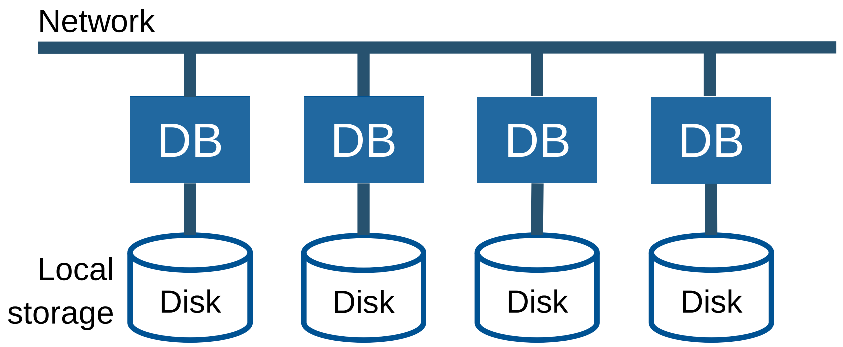
Shared-nothing cloud data warehouse

Shared-nothing architecture

- Shared nothing data warehouse
  - dominant system architecture for high-performance data warehousing.

- Scales well for star-schema queries
  as very little bandwidth is required to join
  - a small (broadcast) dimensions table with
  - a large (partitioned) fact table.

- Elegant design with homogeneous nodes



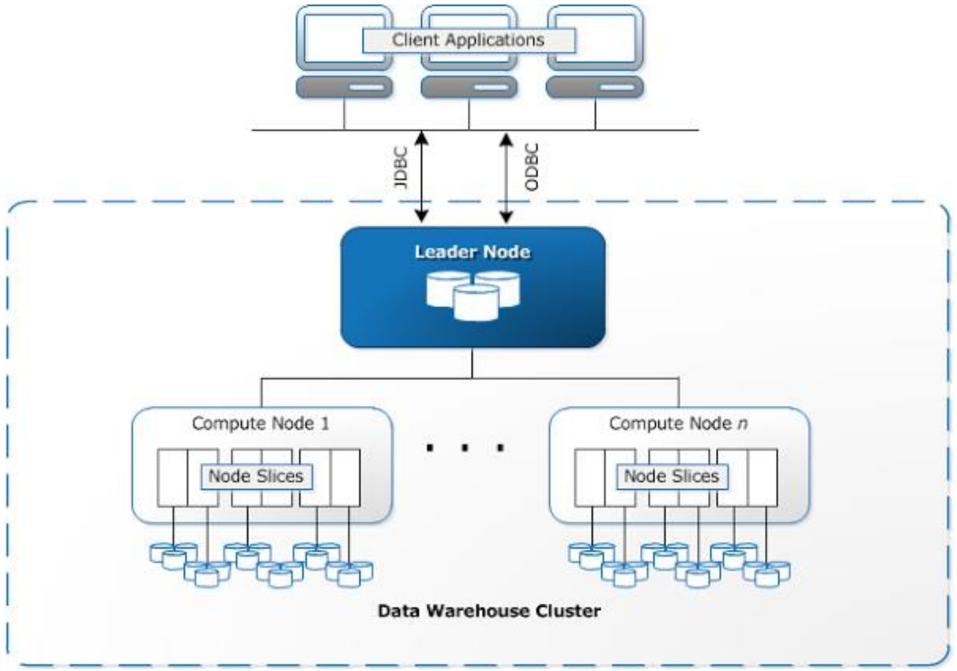
Every query processor node (DB) has its own local attached storage (disk).

Data is horizontally partitioned across the processor nodes.

Each node is only responsible for the rows on its own local disks

Example: old version of Amazon (AWS) Redshift

- Classic **shared-nothing** design with locally attached storage
- The execution engine is ParAccel DBMS
  - **Classic MPP, JIT C++**
- Leverages **standard AWS services**:
  - EC2 + EBS + S3, Virtual Private Cloud
- **Redshift cluster: Leader + Compute nodes**
  - Leader parses a query and builds an optimal execution plan.
  - Creates compiled code and distributes it to the compute nodes for processing.
  - Aggregates the results before returning the result to the client.

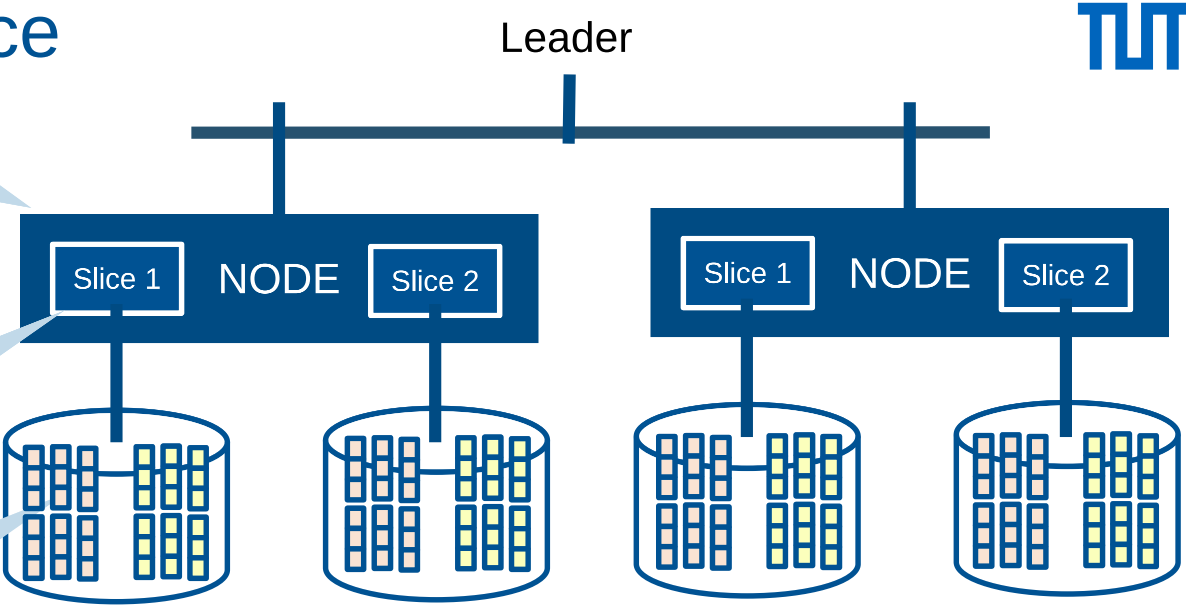


A Redshift Instance

Each compute **node** has dedicated CPU, memory and locally attached disk storage.

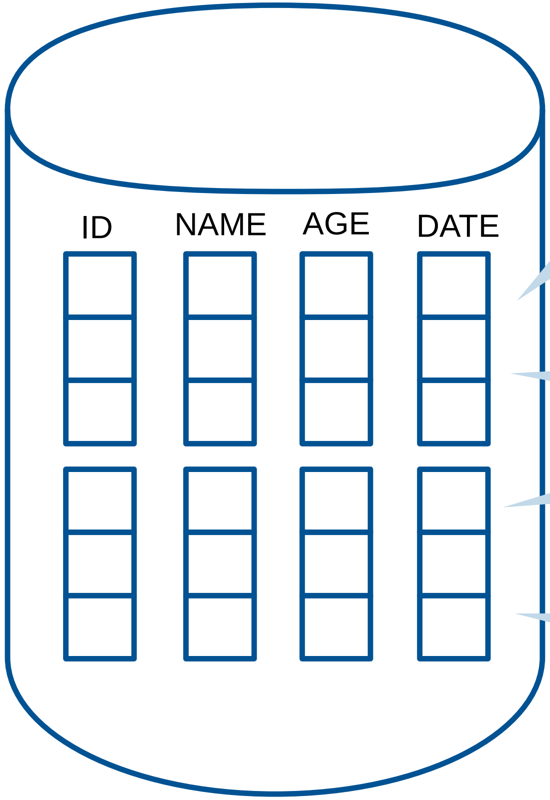
Memory, storage, and data partitioned among the **slices**.

Hash and round-robin table partitioning / distribution.



- The leader distributes data to the slices and apportions workload to them.
- The number of slices per node depends on the node size.
- Within a node, Redshift can decide how to distribute data between the slices (or the user can specify the **distribution key**, to better match the query’s joins and aggregations).

Within a slice



Data stored in columns, sorted by:

- Compound sort key
- *Interleaved* sort key (multidimensional sorting)

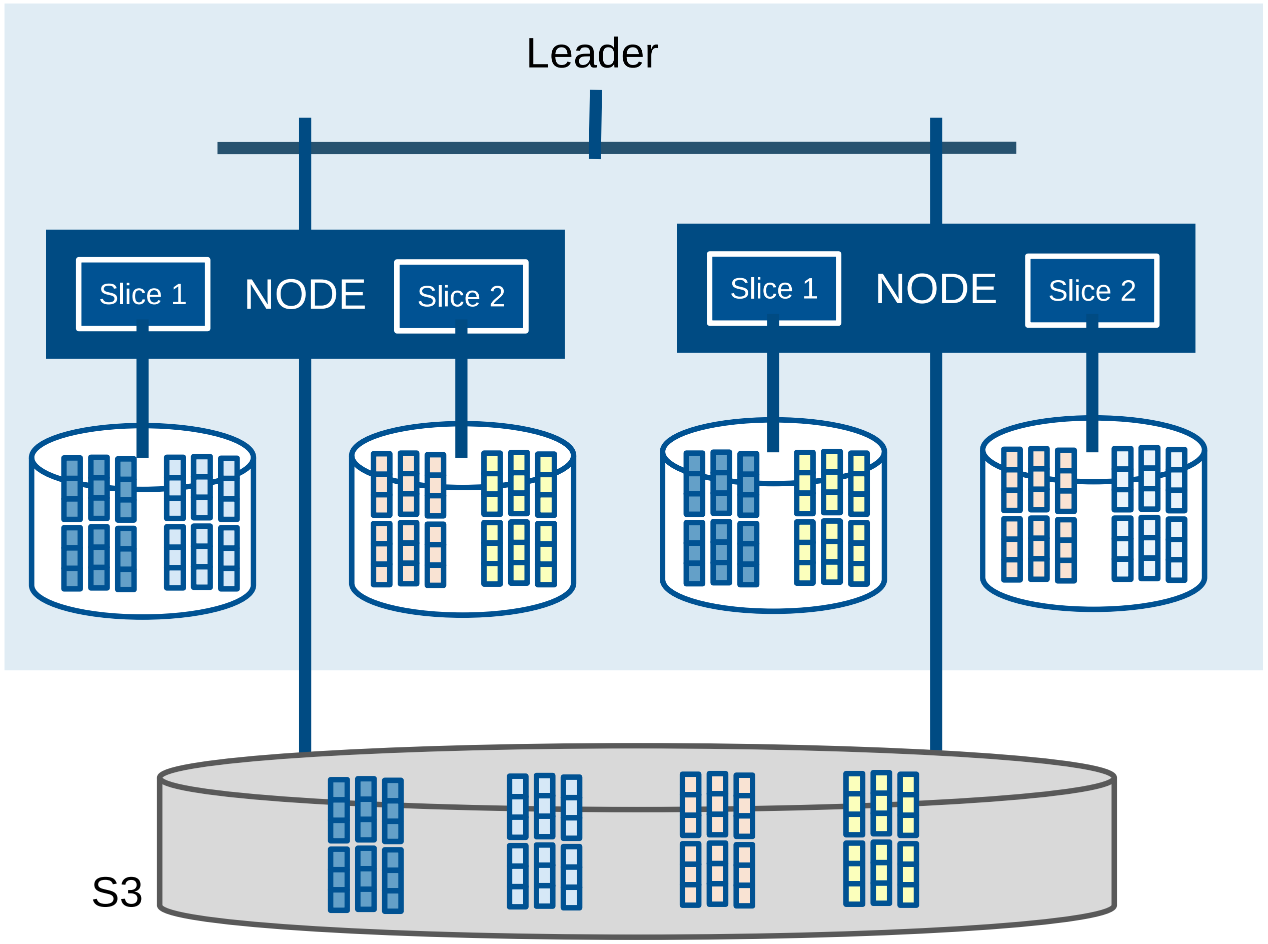
Columns stored in 1MB blocks.

Min and Max value of each block retained in a *zone map.*

Rich collection of compression options (RLE, dictionary, gzip, etc.)

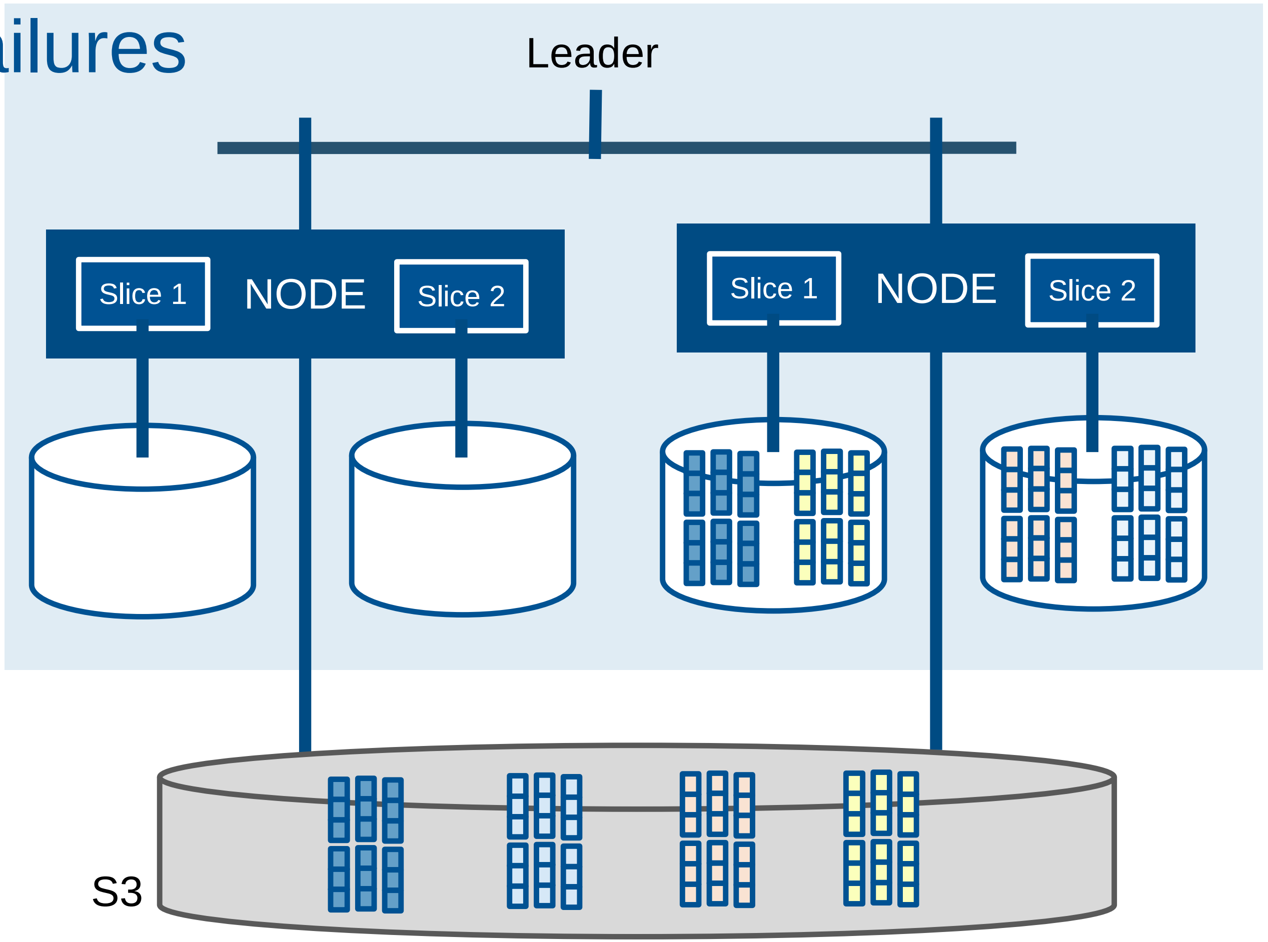
Fault tolerance

- Each 1MB block is replicated on a different compute node
- Data blocks (1MB) are also stored on S3
- S3 triply replicates each block



Handling node failures

- Assume node 1 fails:
  - Option #1:
    node 2 processes load until node 1 is restored
  - Option #2:
    new node is instantiated
    - node 3 processes workload using data in S3
    - until the local disks are restored



Drawbacks of shared-nothing architecture

- **Tightly couples compute and storage resources**

- **Heterogeneous workloads**
  - a system configuration that is ideal for bulk loading (high I/O bandwidth, light compute)
  - is poor fit for complex queries (low I/O bandwidth, heavy compute).

- **Membership changes**
  - if the set of nodes changes potentially a large volume of data needs to be reshuffled

- **Online upgrades**
  - possible but very hard when everything is coupled and expected to be homogeneous.

- This makes it **problematic** to use it **in the cloud setting**

Shared-storage architectures

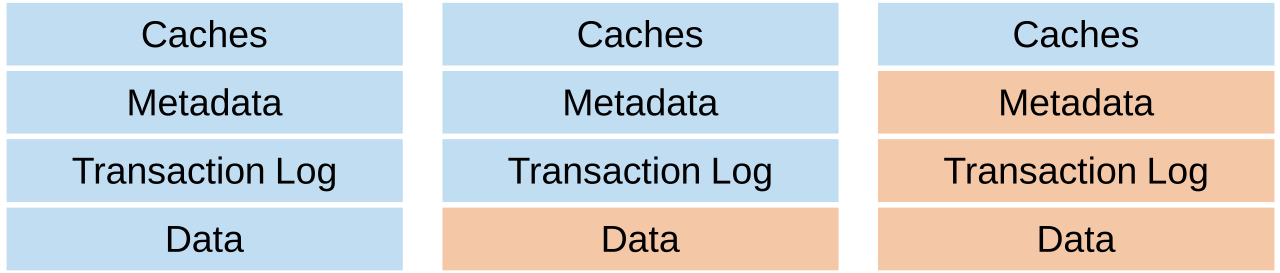
Separating compute and storage

Separating Compute and Storage

- Evolution of cloud-data warehouse architectures over the years

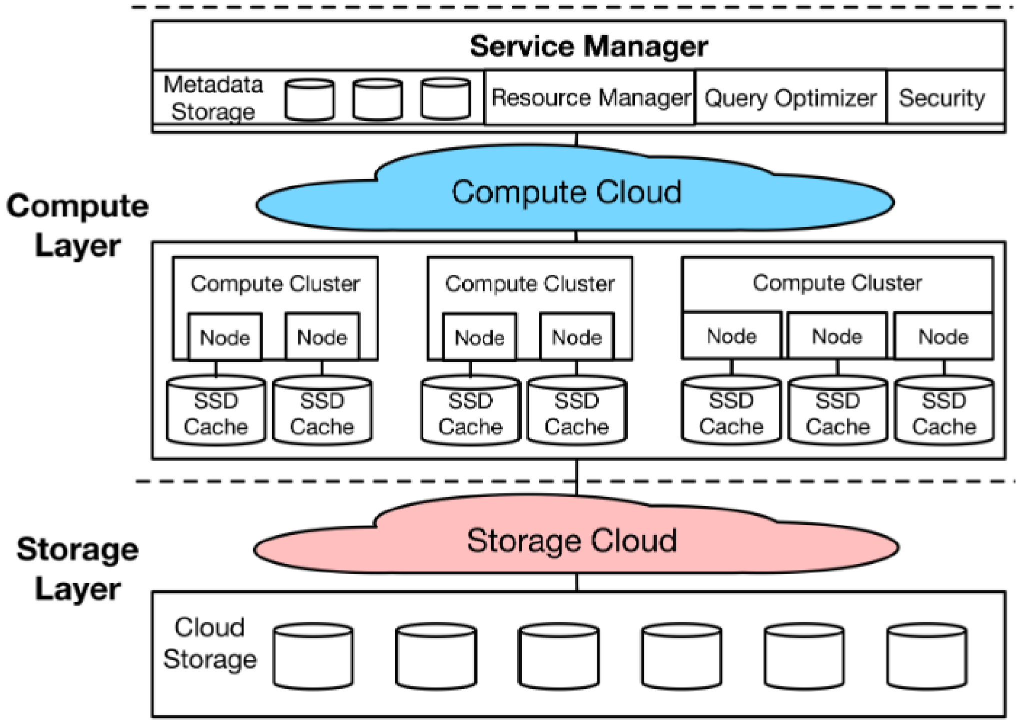
- Engines maintain state comprised of: cache, metadata, transaction log, and data

On-premise architecture **Storage-separate architecture** **State-separate architecture**



- The first step is **decoupling of storage and compute** – more flexible scaling
  - Both layers can scale-up or down independently
  - Storage is abundant and cheaper than compute
  - User only pays for the compute needed to query a working subset of the data

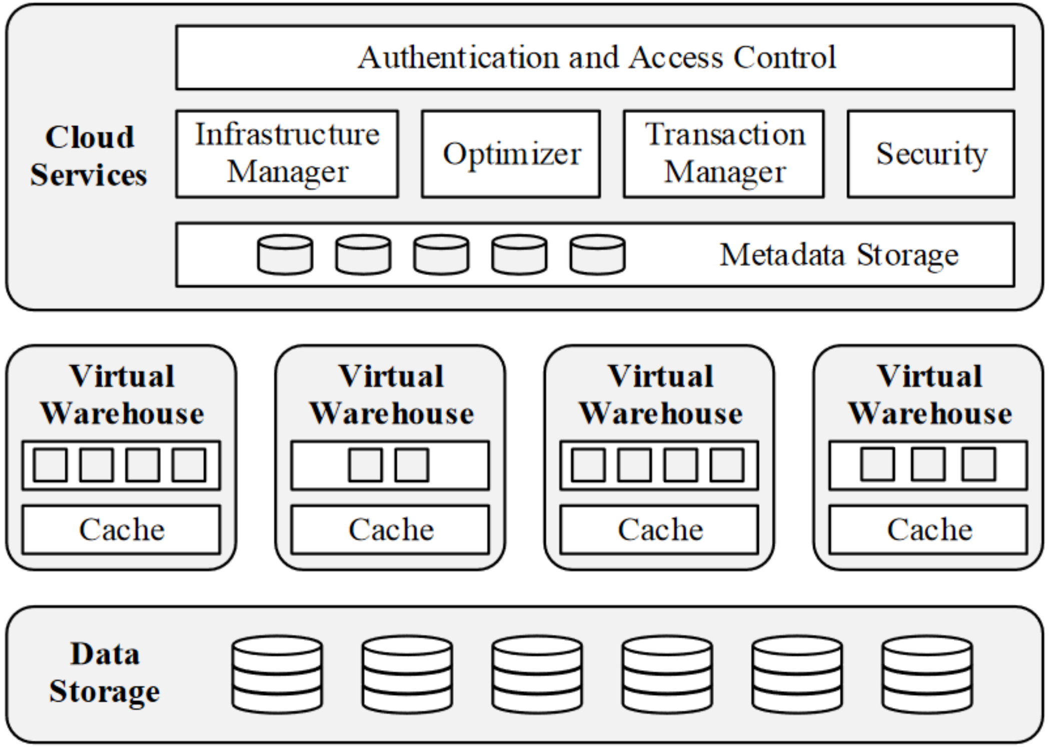
Disaggregated Compute-Storage Architectures



Src: Li et al. Cloud-Native Databases, VLDB'22

- **Advantages:**
  - Elasticity: storage and compute resources need to be scaled independently
  - Availability: tolerate cluster and node failures
  - Heterogeneous workloads: high I/O bandwidth or heavy compute
- **Key features:**
  - Disaggregation of compute and storage
  - Multi-tenancy
  - Elastic data warehouses
  - Local SSDs caching
  - Cloud storage service, e.g., AWS S3, Google Cloud Storage, Azure Blob Storage
- **Examples:**
  - Snowflake, new AWS Redshift

Example: Snowflake



img src: Dageville et al. (2016) The Snowflake Elastic Data Warehouse. SIGMOD

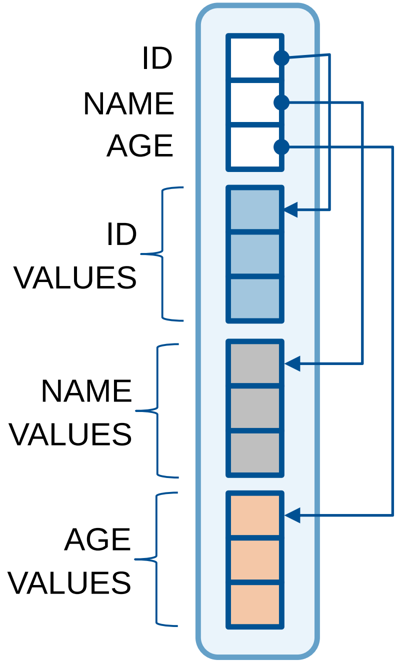
The Brain: Key data management services.

The Muscle: Shared-nothing execution engine (virtual warehouse)

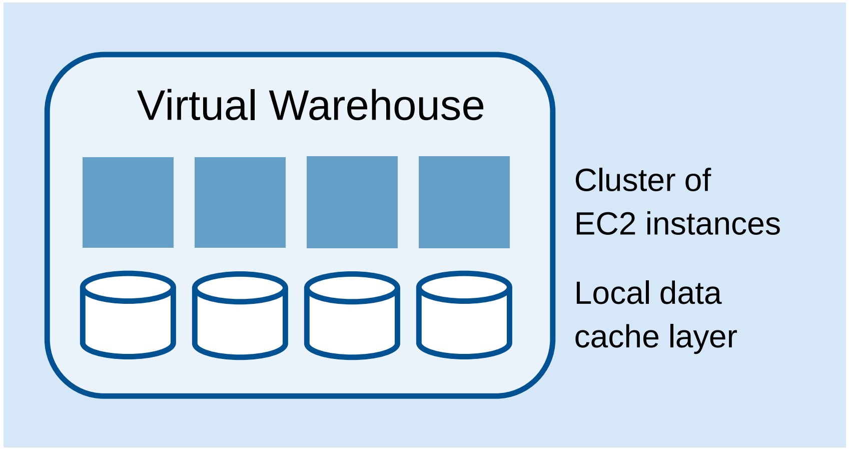
The Storage: Shared-storage for data and query results.

Snowflake's table storage

- Tables are horizontally partitioned into large immutable files
  - Similar to blocks or pages in a traditional database system
- Within each file:
  - The values of each attribute (column) are grouped together
  - Heavily compressed (e.g., gzip, RLE, etc.)
- For accelerated query processing:
  - MinMax value of each column of each file of each table are kept in a catalog
  - used for pruning at runtime.



Snowflake’s virtual warehouses



- **Dynamically created cluster of EC2 instances**
  - Pure compute resources
  - Can be created, destroyed, and resized at any time
- **Local disk cache** file headers and **table columns**
- Three sizing mechanisms:
  - Number of EC2 instances
  - Size of each instance (#cores, I/O capacity)

- Each query mapped to exactly one virtual warehouse
- Each VW may run multiple queries in parallel
- Every VW has access to the same **shared table** without needed to copy data

Snowflake summary

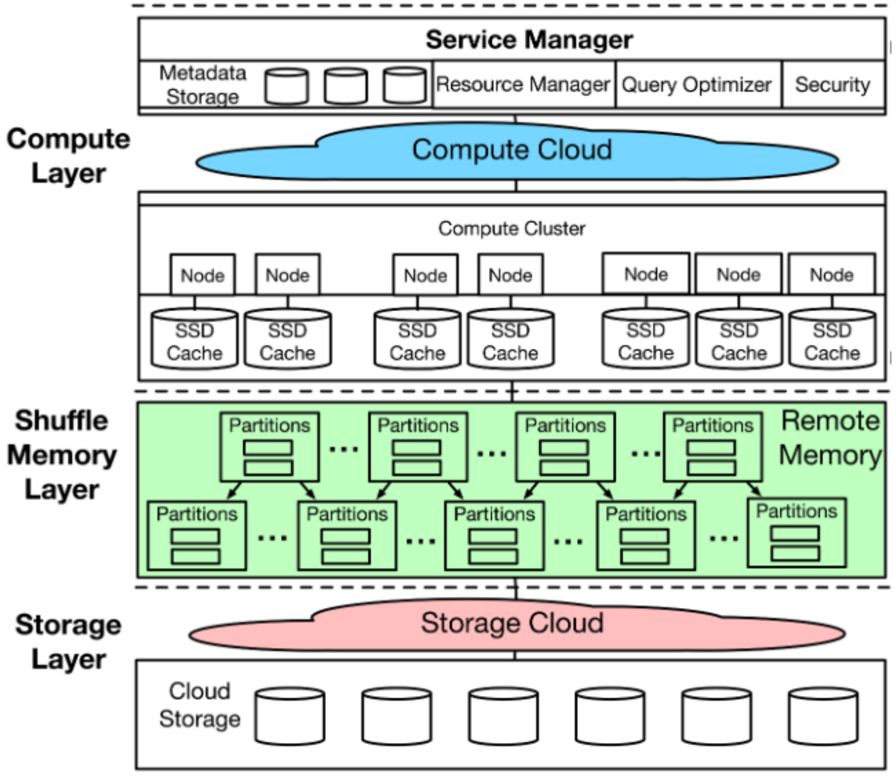
- Designed for the cloud

- Compute and storage independently scalable
  - Data stored in S3/Azure/GFS but with own closed format (you need to load/trasform)
  - Virtual warehouses composed of clusters of compute (AWS EC2) instances
  - Queries can be given exactly the compute resources they need
  - Query execution is still statefull
  - and is not “serverless”

- No management knobs
  - No indices, no create/update stats, no distribution keys, etc.

- Can directly query unstructured data (JSON)

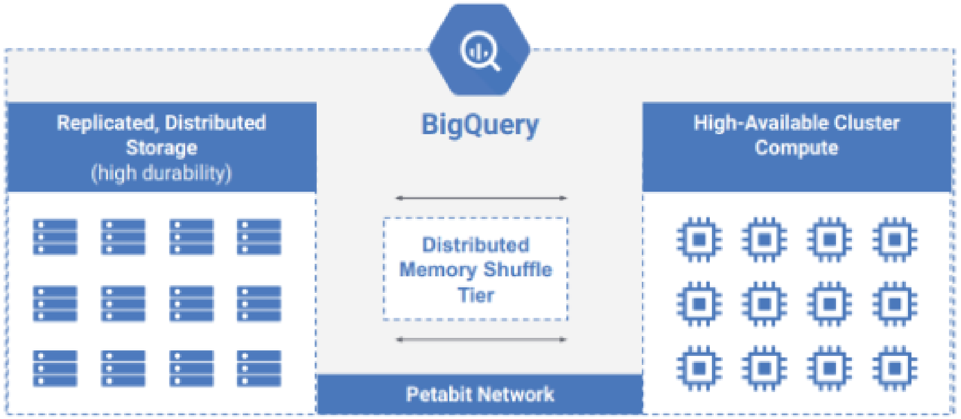
Disaggregated Compute-Memory-Storage Arch.



Src: Li et al. Cloud-Native Databases, VLDB'22

- **Advantages:**
  - Elasticity: storage and compute resources need to be scaled independently
  - Centralized scheduling: schedule the resources for better utilization
  - Complex workloads: cope with the large intermediate results
- **Key features:**
  - Disaggregation of compute and storage
  - Shuffle-memory layer for speeding up joins
  - Multi-tenancy, serverless
  - Local SSDs for caching
  - Cloud Storage Service: e.g., S3, CGS, etc.
- **Examples:**
  - BigQuery

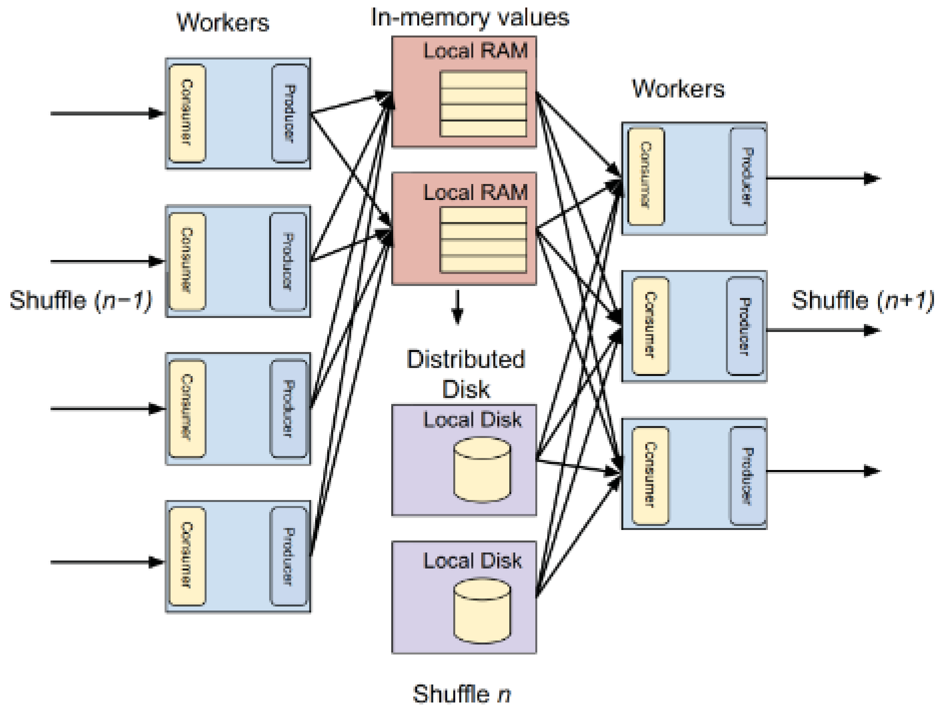
Example: BigQuery


Replicated, Distributed Storage (high durability)
BigQuery
High-Available Cluster Compute
Distributed Memory Shuffle Tier
Petabit Network

Melnik et al. Dremel: A Decade of Interactive SQL Analysis at Web Scale

- **Compute** (Clusters)
  + **Shuffle tier (**Colossus DFS)
  + **Storage**
- **Dremel Query Engine**
- **Distributed memory shuffle tier** for query optimization
  – Reduced the shuffle latency by 10x
  – Enabled 10x larger shuffles
  – Reduced the resource cost by > 20%

BigQuery’s Shuffle Workflow



Melnik et al. Dremel: A Decade of Interactive SQL Analysis at Web Scale

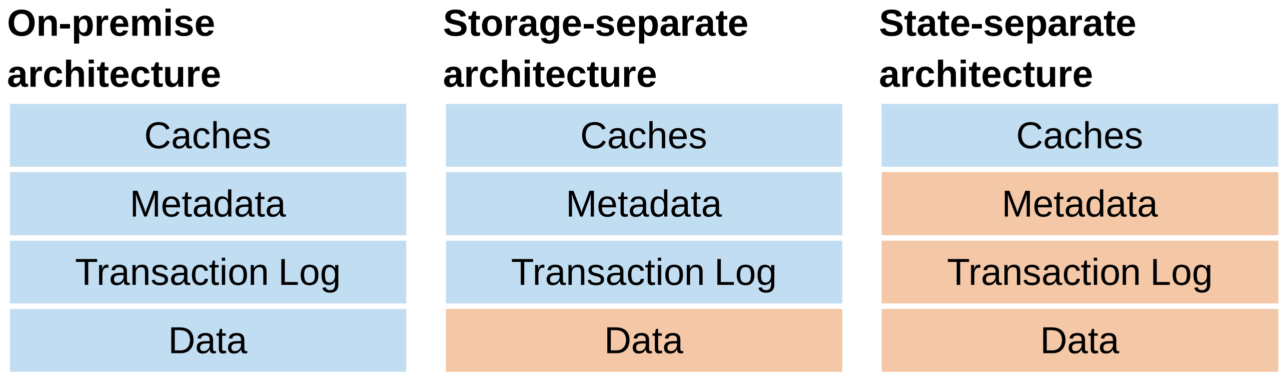
- **Producer** in each worker generates partitions and sends them to the in-memory nodes for shuffling
- **Consumer** combines the received partitions and performs the operations locally
- Large intermediate results can be spilled to local disks

Stateless shared-storage architectures

Separating compute and state

Separating Compute and Storage / State

- In stateful architectures, state of in-flight transaction is stored in the compute node and is not hardened into persistent storage until the transaction commits.



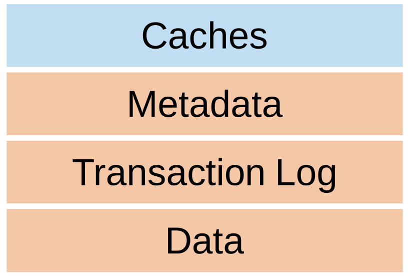
- When a compute node fails, the state of non-committed transaction is lost → fail the transaction

- Resilience to compute node failure and elastic assignment of data to compute are not possible in stateful architectures → the need to move to **stateless architectures.**

Stateless compute architectures

- Compute nodes should not hold any state information

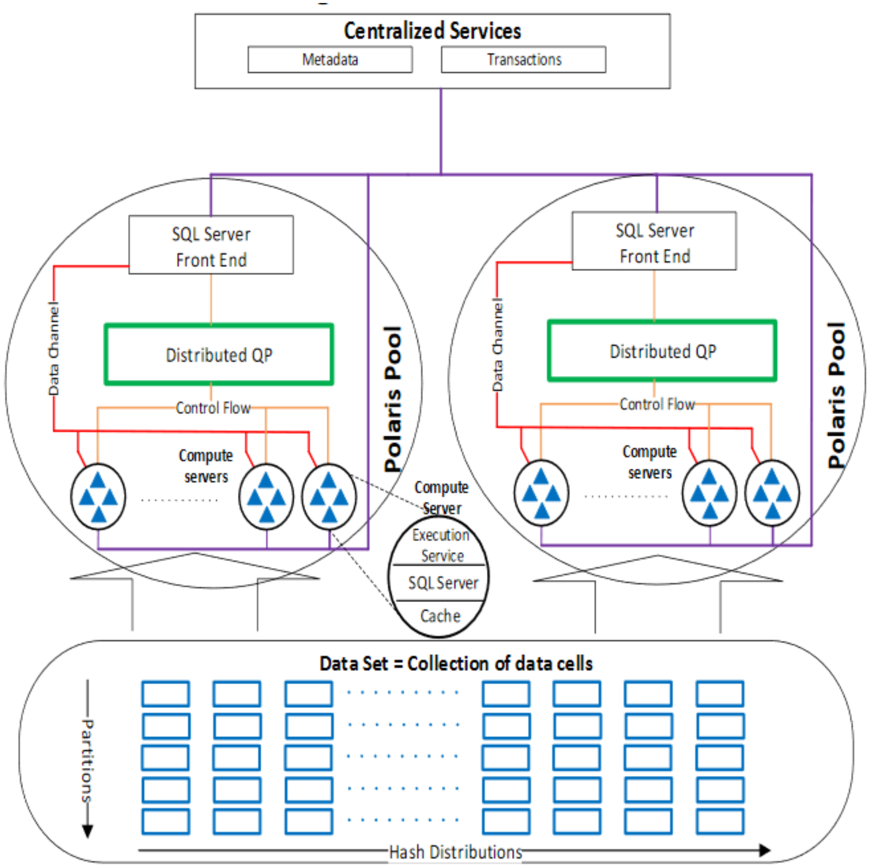
State-separate architecture



- Caches need to be as close to the compute as possible
  - Can be lazily reconstructed from persistent storage
  - No need to be decoupled from compute
- All data, transactional logs and metadata need to be externalized

- Enables partial restart of query execution in the event of compute node failures and online changes of the cluster topology
- Examples: BigQuery using the shuffle tier and dynamic scheduler, POLARIS

Example: POLARIS



- Separation of **storage** and **compute**
  - Compute done by **Polaris pools**
- Shared centralized services
  - Metadata and Transactions
- **Stateless architecture within a pool**
  - Data stored durably in remote storage
  - Metadata and transactional log is offloaded to centralized services (built for high availability and performance)
- Multiple pools can transactionally access the same logical database.

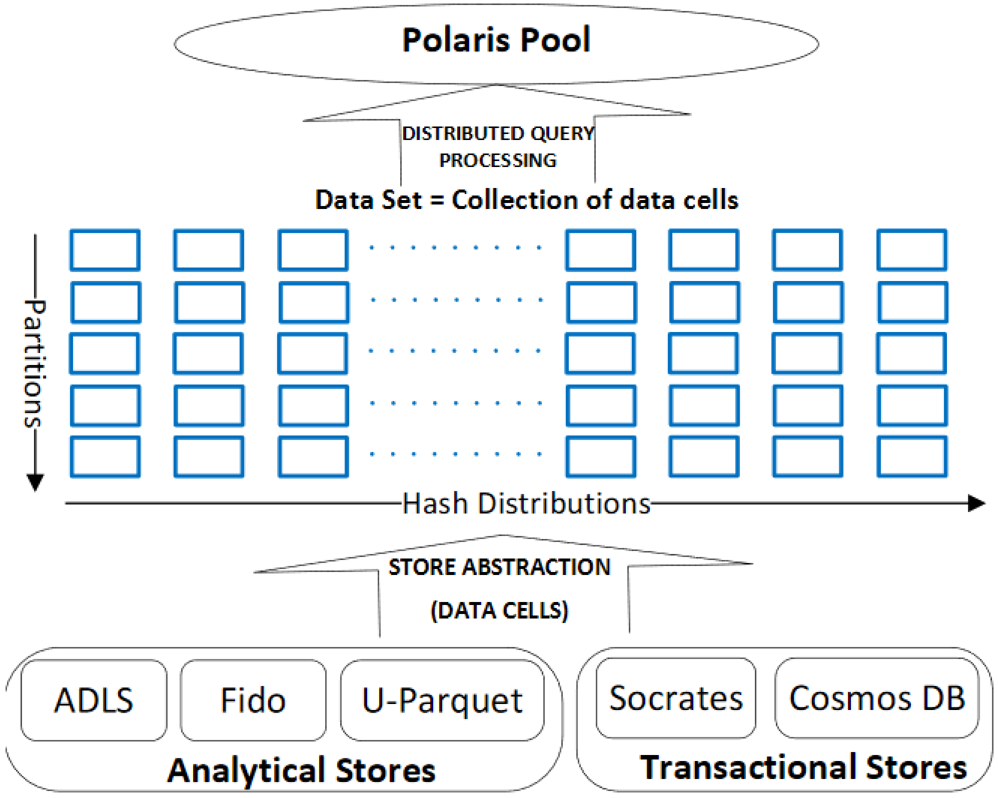
img src: Aguilar-Saborit et al. (2020) POLARIS: The Distributed SQL Engine in Azure Synapse. VLDB

Storage layer considerations

- **Data cells** – abstraction from the underlying data format and storage system
  - Converging data lakes and warehouses

- **Hash-based distribution**
  - To enable easy and balanced distribution
  - Hash-distribution h(r) is a system-defined function that returns the hash bucket (distribution) that r belongs to – mapping cells to compute nodes.

- **The Partitioning function** p(r) is used for range pruning when range or equality predicates are defined over r.

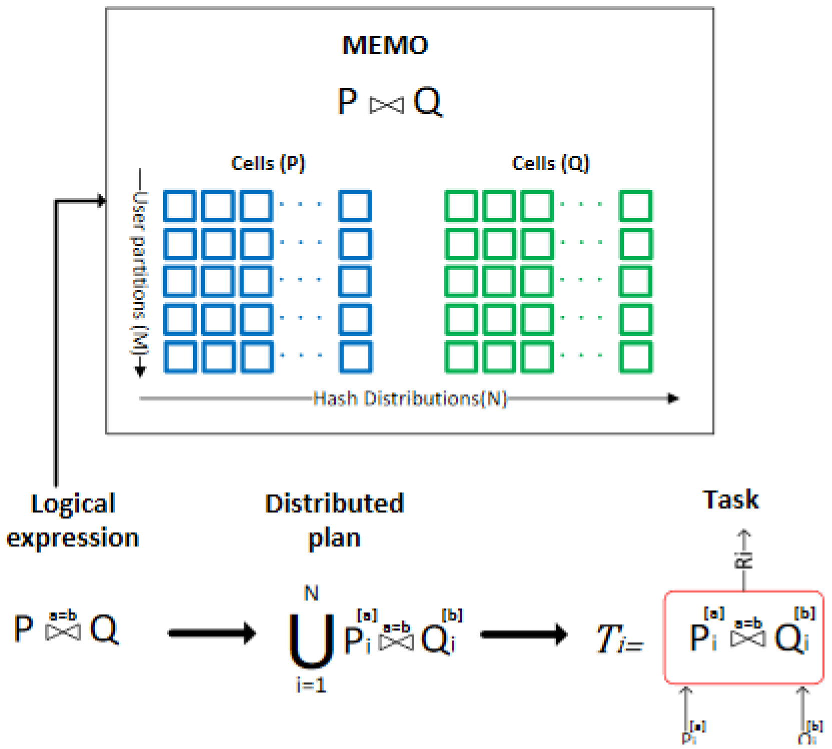


img src: Aguilar-Saborit et al. (2020) POLARIS: The Distributed SQL Engine in Azure Synapse. VLDB

Distributed query processing – part 1

- All incoming queries are **compiled in two phases:**
  - **Stage 1 uses SQL server query optimizer** to generate all logical equivalent plans to execute a query
    - Uses data for the collection of files/tables, partitions, and distributions
  - **Stage 2 does distributed cost-based query optimization** to enumerate all physical distributed implementations of these logical query plans.
    - Picks one with the least estimate cost (taking data movement cost into account).

Task generation in the DQP

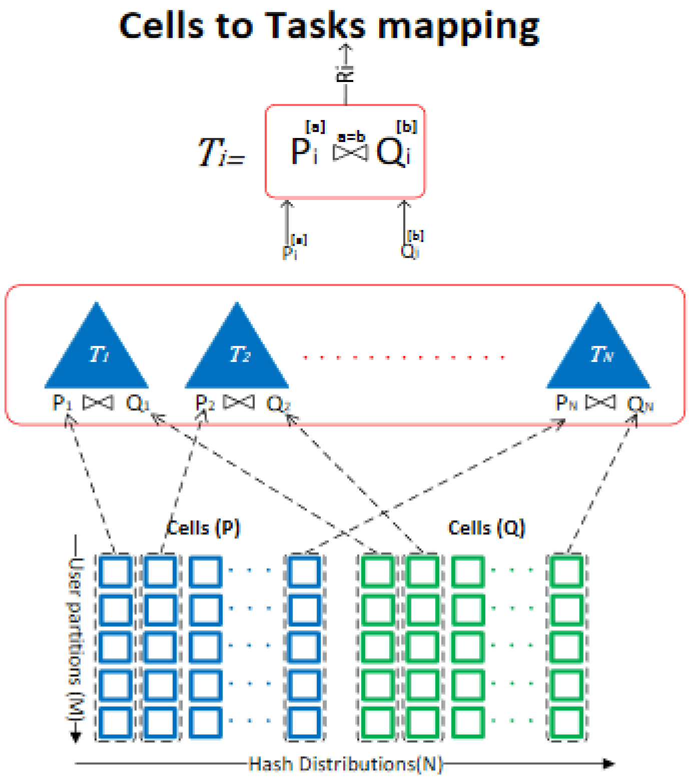


Distributed query processing – part 2

- Task T_i – physical execution of an operator E on the i^{th} hash-distribution of its inputs.

- Tasks are instantiated templates of (the code executing) expression E that run in parallel across N hash-distributions of the inputs.

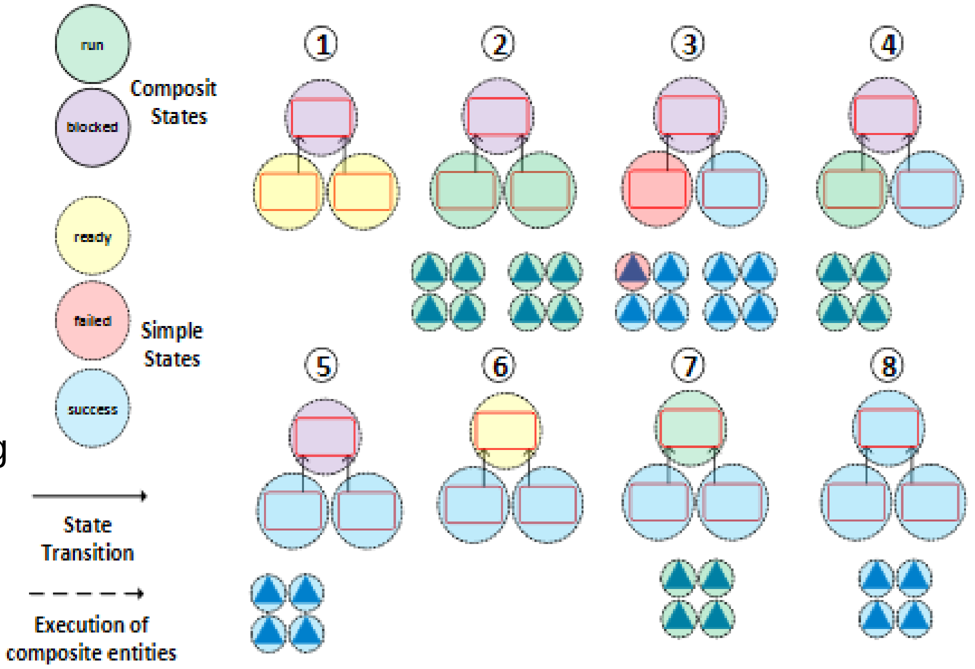
- A task has three components:
  - **Inputs**: collection of cells for each input's data partition stored either in local or remote storage
  - **Task template**: code to execute on the compute nodes, representing the operator expression E.
  - **Output**: collection of cells produced by the task. Used either input for another task or the final result.



Task organization

- **Model the distribute query execution of queries via hierarchical state machines**

- Execution of the query task DAG is top-down in topological sort-order.
- State machines to have fine-grained control at task-level and define a predictable model for recovering from failures.
- States and transitions are logged at each step – necessary for debugging and resuming after failover.
- Low resource overhead for tracking concurrent execution of many queries.



POLARIS Summary

- **The separation of state and compute enable offering different service form-factors:**
  - Serverless, capacity reservations, multiple pools.

- **Data cell abstraction** for efficient processing of diverse collection of data formats and storage systems

- **Combines scale-up and scale-out**
  - **Scale-up**: intra-partition parallelism, vectorized processing, columnar storage, careful control flow, cache-hierarchy optimizations, deep enhancements to query optimization, etc.
  - **Fine-grained scale-out**: distributed query processing inspired by big data query execution frameworks

- **Elastic query processing via**
  - Separation of state and compute
  - Flexible abstraction of datasets as cells
  - Task inputs defined in terms of cells
  - Fine-grained orchestration of tasks using state machines.

Serverless

Serverless Computing for Queries

- Issue queries in the cloud without worrying about resource provisioning and pay by query granularity

- Two main approaches:
  - **Serverless Databases:**
    - Rely on the cloud SQL engine and storage to execute the queries with dynamic resource provisioning
    - The DB service can pause when idle and resume when a query comes in

  - **Serverless functions + Cloud storage:**
    - Rely on Function-as-a-Service (FaaS) and cloud storage to run queries with on-demand resources

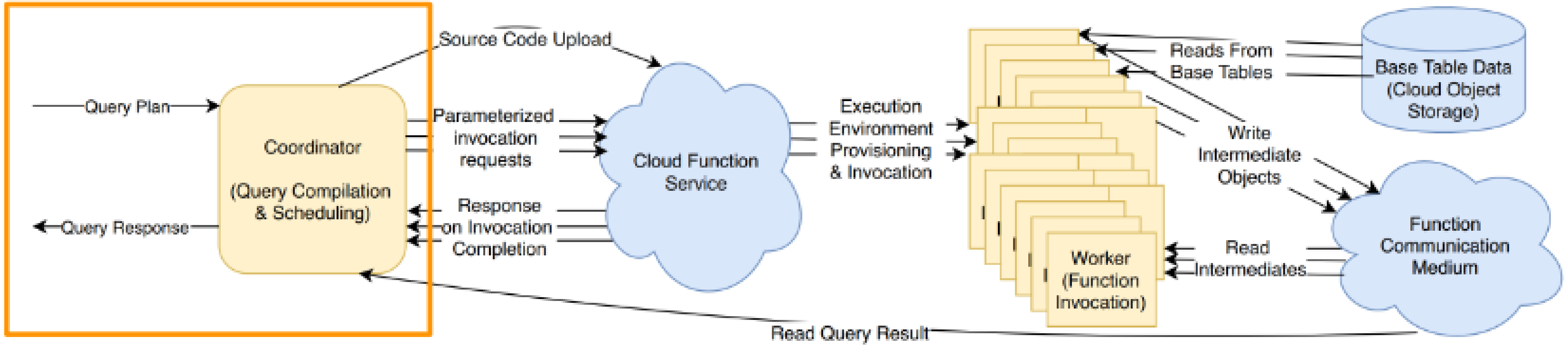
AWS Lambda

Azure Functions

Google Cloud Functions

Serverless Functions + Cloud storage

- **Two challenges:**
  - Functions are **stateless**
  - **Stragglers** increase the overall latency of the parallel query processing
- **Approach:**
  - Use cloud **storage** to exchange **state** → similar to state-separate query processing
  - Use tuned models to **detect stragglers** and invoke functions with **duplication computation**



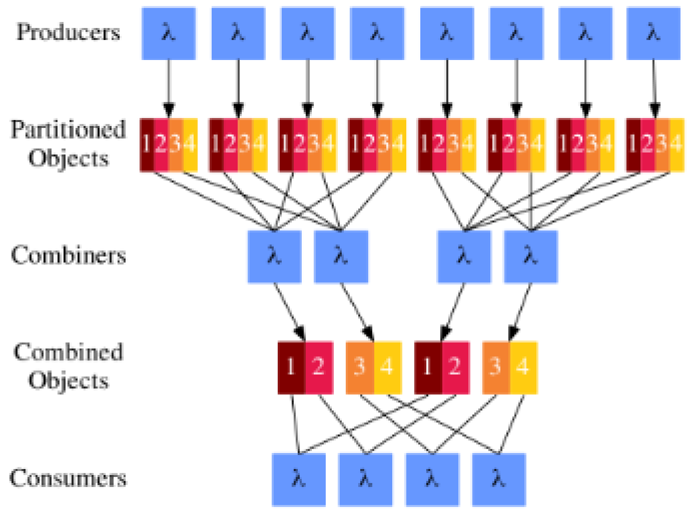
Source Code Upload
Query Plan
Coordinator
(Query Compilation & Scheduling)
Query Response
Parameterized invocation requests
Response on Invocation Completion
Cloud Function Service
Execution Environment Provisioning & Invocation
Worker (Function Invocation)
Reads From Base Tables
Base Table Data (Cloud Object Storage)
Write Intermediate Objects
Function Communication Medium
Read Intermediates
Read Query Result

Perron, Matthew, et al. "Starling: A scalable query engine on cloud functions." *In SIGMOD*. 2020.

Serverless Functions + Cloud storage

- **Query processing using lambda functions**
  - Invoke many tasks in each stage
  - Each task writes the intermediate results to a single object file
  - Combiners can be used to reduce the read cost of the large shuffle

- **Trade-off between the number of invoked tasks (performance) and cost**



Multi-Stage Shuffling based on Functions

Src: Starling: A scalable query engine on cloud functions. SIGMOD'20

Summary of Serverless Computing for Queries

Category	Example System	Approach	Scaling	Pricing model
Serverless Database	Azure SQL AWS Athena BigQuery Polaris	Stateful SQL engine + Auto-pausing and resuming	More CPU, memory or stand-by nodes	Pay for active service with min-max bound
Function as a Service (FaaS)	Starling Lambada	Lambda + Cloud Storage	Invoke more functions	Pay for used fns and storage

References

The material covered in this class is mainly based on:

- Slides from “Big Data for Data Science” from Prof. Peter Boncz, CWI (link)
- Slides from “Tutorial on Cloud-native Databases” from Li, Dong and Zhang, VLDB’22 (link)

Papers:

- Dageville et al. The Snowflake Elastic Data Warehouse SIGMOD 2016
- Aguilar-Saborit et a.. POLARIS: The Distributed SQL Engine in Azure Synapse. VLDB 2020
- Pavlo et al. A Comparison of Approaches to Large-Scale Data Analysis. SIGMOD 2009
- Vuppalapati et al. Building an Elastic Query Engine on Disaggregated Storage. NSDI 2020
- Gupta et al. Amazon Redshift and the Case for Simpler Data Warehouses. SIGMOD 2015
- Amazon Redshift Re-invented. SIGMOD 2022

Further reading:

- Tan et al. Choosing a Cloud DBMS: Architectures and Tradeoffs. VLDB 2019
- Melnik et al. Dremel: A Decade of Interactive SQL Analysis at Web-Scale. VLDB 2019
- Perron et al. Starling: A Scalable Query Engine on Cloud Functions. SIGMOD 2020
- Mueller et al. Lambada: Interactive Data Analytics on Cold Data using Serverless Cloud Infrastructure. SIGMOD 2020
- Winter et al. On-Demand State Separation for Cloud Data Warehousing. VLDB 2022