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Chapter 3: Scalable Data Integration and Distributed Processing Frameworks

3.1. Introduction

The enormous, and still rapidly increasing, volume of data produced and collected by organizations introduces the need for scalable systems that integrate and process this data efficiently and reliably. A scalable data integration framework is primarily responsible for bringing together data from distributed, heterogeneous sources in a way that minimizes the burden on data producers while maximizing data consumers' ability to find and use data for their applications. Reusable, high-quality data can then be made available to users and applications throughout the data life cycle, supporting business intelligence, machine learning, data science, and other tasks. It may even be possible for end users to compose queries on demand without custom integration while ensuring data quality and consistency at query time. Yet these techniques cannot completely satisfy all demands, so data producers are also under pressure to move towards a centralized model, enabling data scientists to more easily share and explore data. The benefits of centralized storage are accompanied by a need for scalable data processing frameworks that can respond quickly to user queries and data-analysis jobs despite the ever-increasing volume of stored data.

To meet this diverse set of requirements, a variety of scalable data integration and processing systems and tools have been conceived and implemented over the past years. The aim of such scalable frameworks is for users to be largely unconcerned about how or where the data is stored and to be able to analyze or visualize the data with minimal delays—either by processing the combined data sets in a single job or by using a gateway to quickly access recently used, central storage. Consequently, integrated system architectures are often characterized by a clean separation of data storage, data management and integration, and data processing, allowing different processing frameworks to be used at different stages of the data-science life cycle and giving systems the freedom to grow in different directions.

3.1.1. Data Federation and Virtualization

Data federation comprises software that integrates queries over distributed, autonomous, and heterogeneous information sources. Data virtualization goes further, providing single-user access, dynamic grouping, and a uniform interface. Federated and virtualized systems are usually combined. Their goals vary from direct presentation of the source information to creation of simple, high-level views for end users. Both involve the same data-integration technologies just described but perform requests on demand.

Federated systems generate a single query for every user request. Query planning, execution, and result assembly occur at query time. A meddler enhances autonomy but incurs cost and significant overhead. A virtualized system prepares data at refresh time, retains it for flash access, and uses it for dynamic groupings. This approach allows for query optimization and prohibits joins across sources. A full virtualized system does both. It combines presentation of directly accessible information with access to more complex, frequently requested, and expensive views. Although simple presentation of the source information preserves autonomy, federation governance is usually implicit. Virtualized systems depend on the data steward for periodic refreshes and correctness when data become stale.

3.1.2. Data Quality and Lineage

Data quality and lineage are tightly interwoven concepts, oftentimes treated as separate disciplines but not rarely coalesced into a single theme. Data lineage focuses on the capacity to trace data back to its origins when published, while data quality aligns with determining the trustworthiness and fitness-for-use of published data and therefore explores the conditions that enable lineage to be established accurately for any given published data. The concept of data quality has elicited voluminous attention – comprising numerous definitions, dimensions, and measurement frameworks – yet it is possible to condense it into a recognizable core: investigation of structural constraints and properties in the data catalogued within a given data management system, irrefutably rooted in metadata exploration, and purposefully defined within a specific data-use context.

Metadata for data quality management and assurance can originate from specialized data profiling and discovery activities or through rules defined by data governance bodies and embedded in data management processes. It is generated and exploited by a variety of systems, including both data discovery and data quality tools. Provenance models are augmented by rules to enable the capture of data quality profiles, conditions, and checks, and apply ontology-mediated queries to retrieve lineage and integrity-constraint metadata from underlying databases, so that captured data quality profiles are natively

stored and exploited in the provenance metadata store. Practical data quality evaluation is aided by the integration of quality information into processes and architectures. Automatic data quality evaluation is ensured through a data quality-as-a-service architecture that utilizes lineage information to minimize the required database accesses. Data quality rules can also be directly integrated within data transformation workflows.

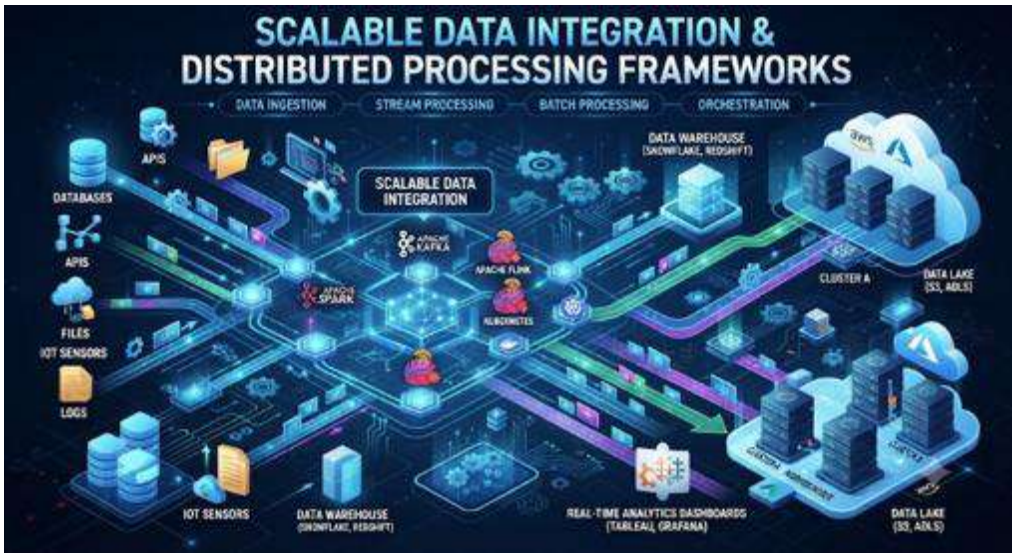

Fig 3.1: Scalable Data Integration and Distributed Processing Frameworks

3.2. Foundations of Data Integration

The core goal of data integration is to create a unified view of data that are generated and stored in different repositories. This objective is achieved by means of a permanently coordinated process composed of the following stages: (i) data ingestion; (ii) data transformation and cleansing; (iii) data integration; and (iv) data orchestration, which governs the execution of the process. Specific data integration frameworks or solutions emerged at the beginning of the 21st century to support this entire lifecycle in cloud environments.

Data ingestion refers to acquiring data from both on-premise and cloud sources and making the data available for further analysis. Several types of data sources can be utilized, including relational databases, document-oriented stores, key-value stores, column-oriented stores, wide-column stores, file systems, and REST services. Multiple connectors are available, each designed to interact with a specific kind of source. Due to the heterogeneous nature of the sources, the discovery and exploitation of their schemas (if any) is a complex operation. As a consequence, schema matching and schema generation represent two central aspects. Dependability is an additional requirement, as

part of the connectors must handle malfunctioning sources by avoiding process failures. Techniques for fulfilling this requirement include (i) redundantly activating multiple connectors for the same source; and (ii) switching to backup sources upon failure of the primary sources.

3.2.1. Data Ingestion and Extraction

The earlier section Analysis of the Prevailing Paradigm within Fundamentals of Data Integration established that a design for any data integration system should be practical, scalable, and feasible to implement and deploy for the majority of use cases one would anticipate in a realistic enterprise scenario. The current section discusses a few of the stages involved in data integration and proceeds to examine available solutions for those stages. The focus falls on data ingestion and extraction. The aims of the next section coalesce around characterizing data transformation and/or cleansing or whole ETL-ish procedures and weigh some of the traditional data integration processes followed in production pipelines.

Information in current enterprise environments is heterogeneous, diverse, distributed, and dynamic. Consequently, the data integration toolbox needs support for the ingestion ofpresent-faceted, present-structure, present-semantic data from these sources. This toolbox requires the implementation of connectors to access data stored in sinkhole solutions without altering the source. It also requires all relevant aspects of a connector's design and implementation to be accessible through concepts usable in realistic environments. One of the most critical aspects of such a connector topology is the support for fault tolerance, particularly at the data source level, since nature is known for being capricious, regardless of the effort in the initial data collection.

3.2.2. Data Transformation and Cleansing

Distributed processing systems often comprise components responsible for data ingestion and extraction, transformation, and movement. Transformations commonly encompass cleansing operations that detect and fix data quality problems, such as the removal of records containing null attributes, the removal of duplicates, or the enrichment of data using external sources. In addition to cleansing transformations, there are data-expanding transformations that take the form of any actions extending the number of base facts, such as denormalization via joins, making the data plentiful and rich. While such transformations may introduce additional complexity to the processing computation and increase the likelihood of failure, they can significantly minimize the number of joins incurred by subsequent analytic workloads and thus increase the overall performance in such systems.

While some cleaner-enriched data are appropriate, users in business intelligence may prefer data transfer with no intentional cleansing (or negative effect), deferring quality control and enrichment in the BI query itself. Moreover, for enterprise data warehouses set up for batch loading, cleansing, and enrichment are typically done as the last steps in data pipelines during ETL. When using ELT within lakes and lakeshouses, the decision of how much cleaning or enriching is performed may vary by analyst, and user tools attempt to make using data-expanding transformations as efficient as possible. Normally, data-cleaning transformations are applied during normalized database-loading steps to normalize data as fully cleaned before archiving them for query performance.

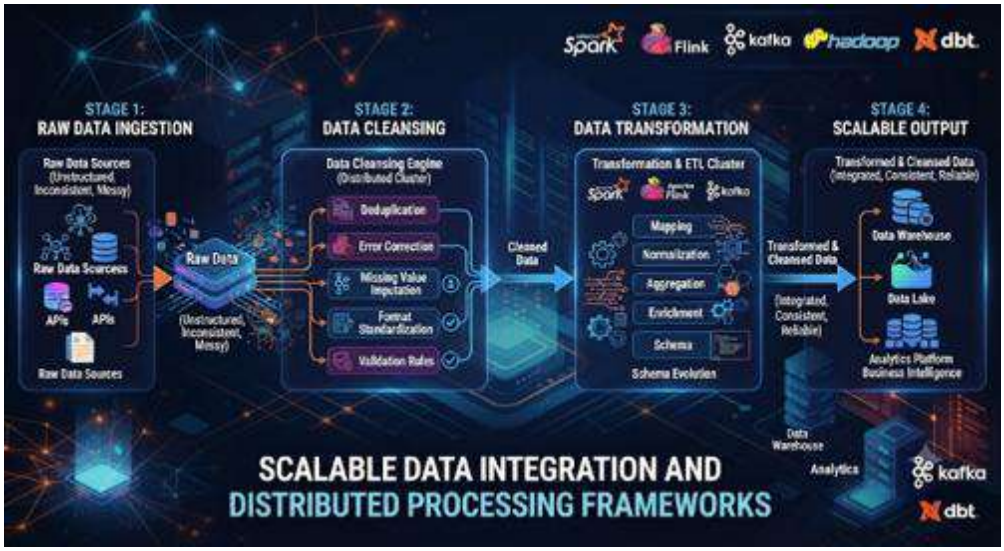

Fig 3.2: Data Transformation and Cleansing

3.3. Distributed Processing Paradigms

Fundamentally distinct distributed processing paradigms have been developed to address specific types of computational problems. Each paradigm introduces a different core abstraction with specialized performance properties in terms of throughput, latency, resource utilization, and failure resilience. The key candidates are (i) batch processing based on MapReduce, (ii) stream processing with windows, and (iii) iterative processing for graph computation. Within each category, individual frameworks exhibit variations that can be matched to appropriate use-case characteristics.

The definition of distributed processing given earlier implicitly assumes a “distributed storage, centralized computation” model, whereby the storage layer is physically partitioned across many machines and the compute framework is responsible for creating, maintaining, and efficiently using these distributed data structures.

3.3.1. MapReduce and Batch Processing

MapReduce is a primitive for parallel processing of large volumes of data on clusters. In its basic form, a dataset is partitioned into splits, which are processed in parallel and the results merged to produce a final result set. The units of work are typically I/O-bound processes that read input files from disk, perform computations, and write the output to disk or query side effects in an external system. During computation MapReduce abstracts the specifics of job scheduling, data distribution, fault tolerance, and resource management. Applications are expressed in a functional style using a small number of primitives for processing arbitrarily shaped key-value pairs.

Batch processing frameworks implement a higher-level abstraction on top of MapReduce: instead of mapping user-specified functions to key-value input pairs, jobs can execute arbitrarily coded workflows using rich APIs, applying optimizations such as job fusion. Scheduling and pre-processing such jobs is generally easier than for low-level MapReduce harnesses. High-level frameworks provide language bindings and editors, simplify data collection and initial processing, and can consolidate MapReduce programs. Availability of an interactive query processor can further facilitate exploration of the data.

A batched processing code path prioritizes throughput over latency. Thus, all jobs are coarsely scheduled and applied to the shared storage layer on as-needed basis. Such multiprocessing concept relies on arranging data so as few jobs as possible are needed to service any query, crunching large groups of similar queries (e.g., for a recency-based recommendation). Under these conditions the throughput, resource utilization, and fault tolerance models of bulk data processing emerge.

3.3.2. Stream Processing and Windowing

Stream processing implements action on live data continuously and is suitable for low-latency scenarios, wherein data is processed shortly after being ingested and thereby offers fast response to upstream changes. The windowing solution is needed for a non-terminating stream of data, as the semantics of windowing define how the input stream is divided into segments, often processing these segments, executing a common pipeline, and then merging the results together. Each operator has some correlation—time or key-based—among neighbouring input records or data, the absence of which may lead to redundancies in computation. For every sequence of input records, the output is typically a mixture of an update and a deletion. The output stream from certain operators typically has either no duplication or at least a constrained cardinality.

The support for windowing solves the aforementioned issues, although a fresh set of challenges now arises.- A continuous stream of events of data containing timestamps

can come from different sources, having widely varied delays. A cookie-press design model replaces the master-slave design of batch processing with a lake-serving-friendly "auto-scaling" model. The resource footprint will be inflated if more copies than necessary of a "hot" service for which data is arriving are in a zone. A scheduling approach reactive to load-driven auto-scaling requests made to an orchestration system by on-demand latency-scaled cluster managers is needed. A cluster manager consistently and effectively remaps the workload from a sink with a record backlog to the standby. Finally, exactly-once-reliability guarantees on stateful stream-processing systems are compared by distinguishing between the common techniques of checking for exactly-once without a strict guarantee and replaying when the internal state message is missing.

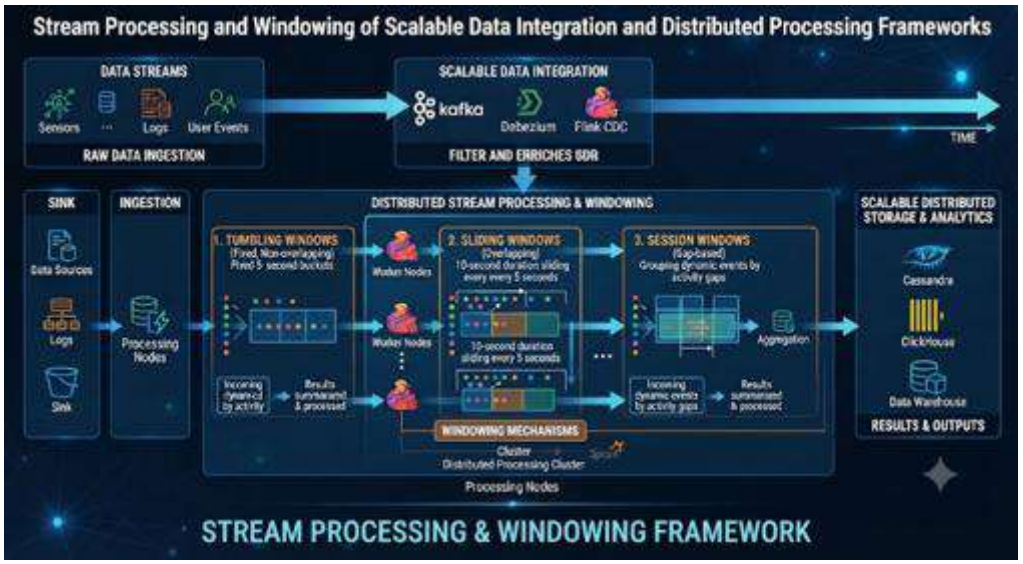

Fig 3.3: Stream Processing and Windowing

3.3.3. Iterative and Graph Processing

Systems supporting iterative and graph processing paradigms are characterized by their requirement to repeatedly execute specific functions on the same, often very large, data set. During each iteration, the results produced in the previous iteration are used as inputs to the next execution. The condition for termination of this cycle is predetermined. Typically, iterative computations require a non-null sharing of intermediate data across iterations, and this can be achieved by storing them in a persistent storage system with access performance characteristics—latency, throughput, and bandwidth—matching those of the cluster's compute nodes. Iterations are processed in a discrete fashion, which may allow other jobs to run concurrently on the storage subsystem. Conversely, the

larger the size of the iterative data sets, the more the iterations resemble long-running jobs, where the sharing of intermediate results is minimal.

Graph processing paradigms are established as a particular case of the iterative one. Computations under this category are defined over graph data structures rather than generic multi-dimensional arrays. In such workloads, vertices are items, while edges provide information on connections and relationships—for example, a friendship graph in a social network, a web graph linking web pages via hypertext links, and so on. The requirement for rapid convergence still holds; otherwise, an iterative processing solution would be machine-optimized. Graph algorithms tend to be very low-level, which makes it hard for users to express what they want. Graph processes present convergence, memory, and computational clichés that, once considered, can simplify the detection of an efficient parallelization scheme.

3.4. Architectural Models for Scalable Frameworks

Architectural models for scalable data integration and distributed processing frameworks must be analyzed in combination, as they jointly determine trade-offs in reliability, performance, and observability. Centralized data integration and distributed processing frameworks can be harmonized into different models that address either data integration or scalability. Significantly less research has investigated frameworks that seamlessly connect both aspects, leading to new potential developments.

Lambda architecture explicitly integrates a scalable framework for federated processing and a physically centralized framework for batch processing into a single model. It consists of three layers. The data ingestion layer integrates a data integration or virtualization framework. The speed layer maintains a physically centralized and replicated query engine that processes a fraction of the data, targeting low-latency requirements. The serving layer combines results from the preceding two layers. Data consistency mainly arises from limitations in the speed layer but can also stem from freshness considerations. Lambda architecture simplifies the architecture for the batch processing part by relying on data stored in a suitable format, albeit at the cost of redundancy and maintenance overhead along the serving layer.

Kappa architecture simplifies Lambda architecture, eliminating the data integration requirement of the speed layer. The framework is particularly suitable for streaming workloads, as raw event data is available and can be processed, replayed, and tuned by a data scientist. The architecture is highly adaptable due to its simple structure but lessens consistency guarantees and increases maintenance costs. The overhead of a storage layer is negligible because of the workload characteristics and the use of an (immutable) indexing system.

3.4.1. Lambda Architecture

The Lambda architecture implements both batch and real-time data processing paths to provide a comprehensive system capable of meeting the strictest requirements in terms of consistency, latency, and throughput. Because the two processing paths operate independently, the architecture can be decomposed and modified more easily than a system where the two paths are tightly coupled.

Data arrives in the system and is partitioned into two paths: the batch path stores the data for later batch processing, while the serving path prepares and serves the data for real-time analytics and decision-making. Real-time analytics and decision-making can rely on the serving path to provide the most current view of the data. When new events arrive, they are simply appended to and then graphically represented in the serving path. In this manner, the service path can provide event-time consistency and the ability to ingest events as they happen.

The event-time characteristics of the serving path can be combined with the higher-throughput batch-processing path to offer low-latency access to the most current view of the protocol data. With appropriate coordination between the two paths, providing the most recent changes from the batch-processing side can be less urgent than the pipeline's remaining service path—the most recent data can be delivered when the batch processing permits.

3.4.2. Kappa Architecture

Kappa Architecture proposes an alternative to the Lambda Architecture that simplifies the implementation of the streaming layer by dropping the serving layer; all data, including history and stream materializations, are available in the ingestion layer to facilitate (re)processing as needed. This consolidation helps remove the data consistency and maintenance issues of the Lambda Architecture, especially if computations are defined in a high-level language and executed on a recording of the event stream. However, it comes at the cost of flexibility—maintenance of a historical state is pursued only if it decreases the overall cost of query execution—or practical economies; rather than organization, the event stream is typically treated as a high-throughput, low-latency mechanism for exposing state updates.

Kappa Architecture is particularly suited for applications with a stream-centric workload, such as continuous anomaly detection or monitoring, since the need to (re)process prior data as new functionalities appear is diminished. Analytics are generally batched with a coarser frequency; doing so on a fast-moving stream—one containing continuous orders, for example—requires careful handling of noise and

duplicates, along with schema evolution and execution on a comparatively weaker resource pool.

In other contributions, the need to unify datasets within a uniform metadata store rubric has been emphasized as a way of constraining the technical implementations at lower levels to allow low-latency query execution. The foundation of multi-layered lakehouses and the Kappa architecture remains separated physical storage and a shared metadata management solution that can to an extent hide the physical implementation from the end user. Such stratification impacts query-blurring complex event processing by separating the strategic data at the serving layer from tactical data sources with shorter real-world relevance.

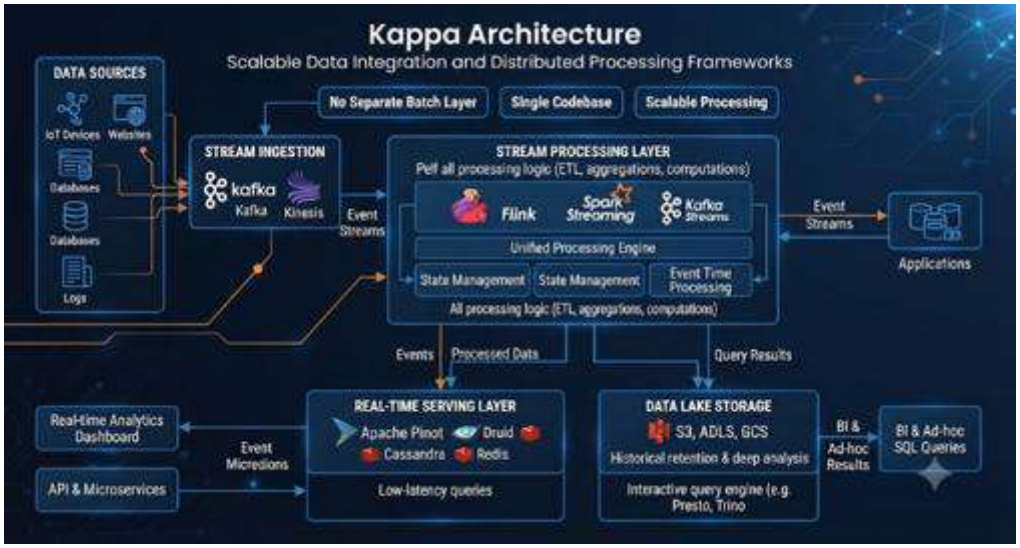

Fig 3.4: Kappa Architecture of Scalable Data Integration

3.4.3. Modern Unified Architectures

Recent years have seen a growing interest in computational systems and frameworks that can accommodate hybrid workloads, including different processing modalities and types of data. An important aim is to establish a clean separation of concerns and responsibilities, enabling intelligent layering and potential off-loading of tasks to dedicated services at different levels in the pipeline.

The lakehouse concept retains the idea of a data lake while adding an access layer for enterprise data warehouse (EDW) capabilities atop the lake storage. Over time, the focus of lakehouses has migrated from optimization of the incoming data path to enhanced performance of the serving layer. The concept is valuable because it supports multiple workloads with a very low data movement cost. It can, however, be expensive to

maintain. Exactly-once guarantees and correctness of the serving layer must be ensured. Other efforts seek to leverage the multi-layered nature of data lakes or use initial stages of the lake concept to create a super-repository for streaming sources without yet addressing the serving layer. Their lakehouse vision is an evolved Kappa architecture; because it treats all input through the same stream-processing-oriented transaction facilities that support low-latency servable-data preparation on all data sources, it becomes a natural fit for container-based processing that supports replaying history or a sub-selection of it.

3.5. Data Storage and Compute Trade-offs

The choice between a processing-centric or storage-centric approach for scalable data frameworks determines the union of physical data layout and logical organization adopted, as well as the computational model employed to perform analysis. In a processing-centric solution, the physical layout is designed to maximize the efficiency of data processing, while the logical organization is dynamic and determined by the query workload. Conversely, in a storage-centric solution, the physical data layout mirrors the logical organization, being static until a new copy of the data is created. Some frameworks decouple physical storage and data processing, creating layered architectures.

Consideration of how data is represented in storage, and how and when it is accessed, can reveal a balanced approach. Layered storage solutions create the greatest separation of concerns, allowing each layer to optimize for a specific aspect of data management and exploit independent scaling. Such separation improves the governance of the data, as each layer can be tuned for specific requirements of data provenance and quality, at the additional complexity cost associated with maintaining multiple different paths through the system.

3.5.1. Storage Formats and Access Patterns

A wide variety of storage formats are available for back-end data storage and each format also allows for unique access patterns. Columnar formats are mostly used with analytical workloads, while normal row-oriented formats are best for transactional workloads. Some formats combine features of both columnar and row-oriented layouts such as Apache Hudi, Parquet and Delta, which are designed to offer support for both analytical and transactional workloads.

Column store formats provide a number of advantages: they allow for improved compression ratios due to better semantic for compressing neighbouring values, they

support better predicate pushdown capabilities since filters can be executed on each individual column, and they allow for fast selective scans, i.e., scanning only a small number of columns. The downside of separating out the columns is that writing the data becomes slower due to the additional overhead and because the write requests span multiple locations.

The data access pattern of a workload primarily decides which data layout would yield the best performance. Row-oriented formats optimized for transactional workloads perform efficient write operations but require that serval rows have to be read from the same location for the query response. Conversely, column-oriented formats are busting the performance of selection queries over a few columns with low number of distinct values due to the very high compression ratios enabled. As a single format does not satisfy both access patterns simultaneously hybrid approaches combining both layouts have appeared.

3.5.2. Storage Layering: Lakes, Warehouses, and Lakeshouses

Cross-architecture aspects of data governance, including security and compliance, become crucial when data originates from multiple—and in particular, untrusted—sources. Data ingestion pipelines typically require a dedicated physical storage layer that supports a data catalog service, be it a dedicated data lake, a data warehouse, or a combination thereof.

Data storage choice is often decoupled from compute resource coordination. Storage is typically centrally managed, and the corresponding vertical scaling is amortized across the complete organization. Storage costs, often viewed as a second-order effect from a compute cost perspective, are also sensitive to data replication (storage often being billed based on the number of stored bytes). Contextual and temporal data sensitivity changes also suggest that data storage can be dynamically spread across cheaper but slower media and faster but more expensive media by deduplication and temporally aware file transfer, respectively. Finally, while cluster managers act as global schedulers for available compute resources, scheduling policies for batch-load-intensive workloads that exploit the operational characteristics of cloud environments are gaining traction. Specifically, scalable resource-aware scheduling policies are receiving increasing attention, given that streaming workloads in particular can benefit from more resources but also, conversely, cost more if idle.

3.5.3. Compute Resource Management and Scheduling

Managing and allocating compute resources for a workload is a non-trivial task, especially to satisfy multi-tenancy where multiple concurrent workloads share the same resources. For data intensive workloads, resources are often allocated at a coarse granularity; so besides fast creation and allocation of jobs, idle resources also need to be freed when not used for a while. Autoscaling on a cluster level can ensure that the cluster is sized according to its usage and costs are minimized. Finally, workloads can also be optimized based on the resources allocated to them through resource aware scheduling policies.

3.6. Conclusion

The overall goals of scalable data integration and distributed processing frameworks are to aggregate information from diverse entities and execute computation on large datasets. The increased availability and diversity of data have attracted many private and public stakeholders offering scalable tools, services, and platforms. Despite the growing popularity and adoption of these frameworks, both the integration and processing aspects present intricate trade-offs that impact their suitability, efficiency, and utility for given workloads. A systematic comparative assessment exposes key phenomena and associated metrics, guides the selection of general-purpose tools, and inspires tailored solutions in specific domains.

The foundations of data-integration frameworks have been extensively studied in theory and practice. Research on data-processing paradigms has produced a rich body of literature as well. Understanding the underlying principles fosters a more nuanced appreciation of existing tools and inspires new solutions. Notable explorations encompass the comparative study of data-integration services, MapReduce and batch processing systems, stream-processing services supporting windowing semantics, iterative and graph-processing frameworks. Further analyses delve into the systems-building landscape, integration, storage, processing, and access trade-offs associated with the Lambda, Kappa, and modern unified architectural models.

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