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Chapter 4: Distributed Big Data Processing and Storage Architectures

4.1. Introduction

As numerous businesses are transforming their operations towards the cloud, the ongoing cloud-native revolution draws attention to their next architecture evolution. The booming cloud-native ecosystem provides a wealth of cloud infrastructure services supporting cloud-native applications. However, their ongoing growth tests many of these technologies' reliability, scalability, and availability. Even for mission-critical applications that still run on on-premises data centers, their production-ready implementations often make use of open source or proprietary technologies that are in the cloud-native ecosystem.

The ever-increasing amount of data under management within cloud-native applications demands new data processing and storage architectures to meet their scalability, availability, and elasticity requirements. Distributed systems offer the solution. A system that comprises multiple components located in different networked computers but that appears to its users as a single coherent system is commonly referred to as a distributed system. Distributed systems have become the architectural pattern of choice both for the development of large and elastic applications and for the management of large amounts of data. Whereas distributed system architectures manifest multiple processing and storage components, distributed data system architectures concentrate on the storage and processing of data.

4.1.1. Background and Significance

The processing and storage architectures used to effectively manage very large data sets must span thousands of machines, combine many different kinds of hardware and software, and be scalable to many different sizes. Much of the underlying infrastructure used by modern Web applications derives from the efforts at Amazon, Google,

Microsoft, Facebook, and other companies, motivated in large part by the need to support and analyze large amounts of data generated and used by their services. Yet these systems are also relevant to other industries that need to analyze large logs of data or enable new kinds of applications such as machine learning, data mining, or question answering.

Three trends make such approaches desirable: the continuing advances in storage and processing cost, the maturity of effective fault-tolerance strategies, and the relative absence of complex and expensive HW/SW dependencies that hinder distribution. The massive quantities of data being collected enable storage-level replicas for high availability and data redundancy, while the industry adoption of a simple and efficient replication strategy has made it possible to deploy large clusters of inexpensive commodity machines. As a result, the focus has shifted from traditional data replication to the efficient management and real-time analysis of high-throughput streams of events generated by user activity. Such systems can be modeled and reasoned about using traditional techniques for distributed systems.

Fig 4.1: Distributed Big Data Processing and Storage Architectures

4.1.2. Research design

The main trend in the digital world is the consolidation of data behind large companies and corporations that manage public services on their behalf. However, frequent data leaks, misinformation campaigns, and a digital divide raise concerns among scientists,

companies, and the general population. Consequently, attempts to decentralize information originate from a range of initiatives, known collectively as Web3. Another trend is Big Data, which is now closely connected to Artificial Intelligence. New tools and processes make use of massive volumes of varying data in order not only to teach machines but also to generate predictions, recommendations, and intelligent decisions. This research seeks to explore Distributed Big Data Processing and Storage Architectures.

Distributed big data processing combines foundational models, infrastructure, and paradigms into a coherent whole. The main digital architecture enables the management of a large number of data sources generating enormous volumes of information moving in various forms and flows. First, the basic elements involved in the operation of distributed information systems are examined, covering data models and storage topologies, consistency/availability/partition tolerance (CAP) properties, and distributed storage architectures. Next, distributed data processing frameworks are targeted, especially batch processing paradigms. The third area of investigation covers data ingestion, movement, and integration, considering the role of message queues, data pipelines, and orchestration. Finally, strategies for ensuring consistency, reliability, and fault tolerance are assessed, including data replication and storage snapshotting.

4.2. Foundations of Distributed Data Systems

Distributed systems encapsulate a wide range of applications and technology. Therefore, it is imperative to analyze the foundations of distributed storage and processing systems in detail, addressing the capabilities and limitations of each component of the system, the interactions between the components, and how various solutions work together to achieve common goals. The presentation is organized based on the classification of data systems into four broad categories: distributed storage; data ingestion, movement, and integration; distributed processing; and consistency, reliability, and fault tolerance.

Similar to any other data system at any scale, distributed data architecture must also address the fundamental question of how data is modeled and how it affects the underlying architecture. Within distributed systems, the choice of data model and storage technology often manifests trade-offs in consistency, availability, and partition tolerance, forcing application developers to select the technology that best suits their requirements. These choices, in conjunction with the widely adopted principles of data locality and shared-nothing architecture, drive the design of storage architectures, the adoption of batch or stream processing styles, and the development of specialized technologies for data ingestion and data movement. However, the massive size and rate of data generation, coupled with the absence of a singular organization, have also

inspired the introduction of object stores, immutable ledgers, and protocols such as Apache Kafka.

4.2.1. Data Models and Storage Tashapes

The first step in the analysis of distributed big data systems is to define the data foundation. At the data model level, there are several options. The most widely used analytical data model consists of multidimensional tables with attached metadata. The low-level data shape used by distributed storage systems differs widely, ranging from immutable logs to nested objects. In addition, there are predefined virtual shapes that make large-scale data querying easier, such as data lakes or data warehouse models. When Big Data systems draw the initial conceptual distinction between technologies that do best with batch processing versus streaming mode, the difference is evident at the data model level. Batch operators work on organized, stable data stored in tables, while streaming operators work with semi-structured nested log shapes, supported by efficient windowing mechanics and late-arrival strategies.

Distributed processing frameworks belong to one of two paradigms: batch processing or stream processing. Batch processing performs big computations in a single run on a voluminous dataset that is stable and organized in a table-like shape. The input is read from the underlying immutable storage and the output is stored in the same or a different distribution storage. The processing is performed in batches on data stored in tables. Stream processing provides real-time analytic capabilities, detects events and changes, and enables interaction with systems or humans. The input contains the most recently ingested data in a nested shape and is read in chunks, with data added at high frequency and with a semi-structured shape that is inherently unstable.

4.2.2. Consistency, Availability, and Partition Tolerance

The distributed nature of big data processing systems introduces additional challenges related to fault tolerance and data consistency. In particular, the CAP theorem formalizes the trade-offs between consistency, availability, and partition tolerance in a data system. The theorem states that a distributed data store can guarantee only two of these three features at a given time. Consistency requires that every read returns the most recent committed update to the object or an error. Availability ensures that every request (read or write) receives a response, regardless of the state of any individual node in the system. Partition tolerance allows the system to continue operating despite arbitrary partitioning due to network failures or other causes. In practice, some form of trade-off is often necessary; most key-value stores provide a weaker consistency model in favor of improved performance and availability during network partitions.

Distributed big data systems rely on object-based data models that define different data structures for different components. Data storage rely on key-value stores or wide column stores modelled into a partition, replication strategy, and consistency protocols. Two groups of consistency protocols are present in distributed big data systems: read-your-writes, eventual, and causal consistency; distributed transactions and consensus protocols.

4.3. Distributed Storage Architectures

Key data management challenges involve designing storage systems and data movement patterns that are appropriate for the data sets and workloads, and that fulfil the demands of the applications and external systems connected to the Big Data architecture. Although storage shapes may be application-specific, systematic patterns exist in the architectures of large distributed data stores. In general, open-source storage systems can be grouped into two major types: those simulating traditional object storage and those reproducing the functionalities of traditional file systems. The relationship between the data processing approaches outlined earlier and these two major types of data storage architectures is not one-to-one: log-oriented storage systems can efficiently model and reproduce the functionalities of both storage types, and even now there is a number of both type implementations under development or consideration.

Fig 4.2: Distributed Storage Architectures

Systems using the object-storage abstraction are the most common, and include well-known and widely adopted systems such as Amazon S3, Ceph, and OpenStack Swift. Implementations of object storage and log-organized storage use similar storage shapes and models, but present a distinct set of functionalities: the first are intended to hold static datasets, the second to manage the movement of temporal data. In a way, log-

oriented architectures can be seen as dynamic and continuously updated representations of static object-storage-like systems, even though they also enable temporal query capabilities.

4.3.1. Object Storage and Immutable Ledgers

Object storage systems treat files as opaque, contiguous binary data identified by globally unique identifiers, avoiding the need to maintain a directory tree. Data blocks are distributed across a cluster of commodity hardware using erasure coding for redundancy, efficiently supporting multi-tenancy. REST-style application programming interfaces (API) such as Amazon S3 allow easy access over the internet. Multiple cloud providers have cloud storage services for external access, while systems such as OpenStack Swift provide cloud storage infrastructure for internal cloud-based service offerings. Data-agnostic design enables accommodation for large datasets in geo-distributed environments, allowing user-defined placement policies for data proximity and access optimization.

Systems that rely on append-only and immutable writes provide unique properties. Changes are recorded as new, immutable writes rather than overwrites. Append-only writes untangle update and read workloads, facilitating efficient data movement between storage tiers. By allowing new writes to avoid searching for free space in data structures like B-trees, high-throughput ingestion becomes easier. Furthermore, applications that support time-travel queries and simplify onboarding through low-latency writes become possible. Systems that support these properties, often referred to as immutable ledgers, are typically used to host events or primarily write-once data.

4.3.2. Distributed File Systems

Distributed and multipurpose file systems designed to provide scalable storage services suitable for a range of analytic workloads.

Distributed file systems (DFS) were introduced to offer a shared mutable state to large user communities in the form of a coherent name space, simple user-accessible APIs, and consistency guarantees. The important aspect of the security updates conceptually lies in offering the same read-after-write consistency guarantees returned by a single copy system. A DFS typically enables data items to be accessed concurrently and updated in a controlled manner. Systems such as Google File System (GFS), Hadoop Distributed File System (HDFS), GlusterFS, and LustreFS emphasize performance for utility computing, whereas systems such as Lustre, GFS, and HDFS are optimized for throughput.

GFS and HDFS highlight the following principles: Google and Hadoop users process vast amounts of data on clusters of thousands of nodes in a fault-tolerant manner; thus, applications read data many times versus writes. New writes are infrequent and come in large streams into the system. InGoogle, a finite number of “clients” append to a small collection of files and want immediate visibility of changes, such as logging. The system obviously supports an append-left, append-right type of access for both logs. Updates originate from a small number of clients and have similar semantics to removing/moving.

4.4. Distributed Processing Frameworks

Big Data systems are frequently analysed in terms of a layered architecture. Given the separation of concerns that has emerged, such an analysis is particularly relevant for how data is processed, moving from batch jobs to real-time execution and event handling, all orchestrated by integration pipelines based on rules and conditions.

Batch processing has traditionally driven large-scale data processing, driven by the need to run resource-intensive jobs for data mining or analytics. Distributed processing systems (DPS) break data into smaller subsets, allocating the subsets to a large number of processing nodes to improve runtime. The Hadoop ecosystem epitomises this approach with parallel data processing framed as ‘Map-Reduce’. More recently, novel techniques such as DAG scheduling have combined the benefits of the parallelism of DPS with the low-latency requirement of Interactive Query Systems.

Distributed Real-Time Processing Systems (DRPS) are similar libraries that facilitate on-the-fly updating of output data. However, they tend to have a narrower focus, optimising Big Data for Event Stream Processing and Complex Event Processing. Rather than supporting batch jobs given specific data queries, DRPS execute pipelines with continuously running jobs, forming the basis for data stream and event stream processing. Rather than implementing an explicit data ingestion mechanism, DRPS acquire data by connecting the operations of their jobs to the output of an upstream job.

4.4.1. Batch Processing Paradigms

Batch processing enabled by the MapReduce paradigm is probably the most well-known and recognized approach to distributed big data processing. The introduction of Hadoop popularized the original MapReduce paper [39] and led to the establishment of a large ecosystem based on Hadoop Distributed File System (HDFS) for persistent storage. As a consequence, other data processing frameworks and tools such as Hive, Spark, or Flink later surfacing resulted from further enhancing these paradigms by extending their

capabilities on the processing front—starting from SQL-like encoding representing query abstractions (Hive), in-memory processing optimizations (Spark), or support for different storage backends (Flink)—all while relying on underlying batch-oriented capabilities provided by Hadoop during their processes.

Google's Dremel offered a different approach by adapting batch query processing to interactive query processing and reporting against commonly updated data. The successive rallying of compute engines under the SQL-on-Hadoop umbrella, together with Dremel and its interactive nature, along with the Map-Reduce paradigm emerging as a batch approach to distributed big data processing, consolidated this constellation of systems. Batch-oriented processing paradigms thus achieved the highest degree of acceptance in big data environments, with varied use cases and interesting reports of successes, pioneered and backed by industry acceptance, often exemplified through industry use cases first reported in the literature.

4.4.2. Stream and Real-Time Processing

The volume of data exchanged every day is increasing tremendously, providing societies and companies with unique opportunities to deliver streams of events about their reality. Such events can be in the form of clicks on a website, telemetry generated by sensors in connected cars, logs produced by service applications, mobile phone text messages, trades between users in a stock market or cryptocurrency network, and more. Even though recent event-stream applications are interconnected with a dynamic structure, they mostly work at a smaller scale. However, these relatively small applications have been the backbone of major companies. They present the potential to attract users and grow fast, consequently generating enormous amounts of events. Millions of dollars have already been invested in building larger-scale data-centric applications with streaming requirements at companies like LinkedIn, Netflix, Uber, and Pinterest. The need to manage these applications at scale led to the first streaming platforms. These platforms exist to deliver, process, and link events coming from divergent data sources in increasingly rich ways.

Event streams are an implementation of the publish-and-subscribe model. An event can have one or multiple producers that propagate the events to distributed remote networks known as brokers, which regulate consumer access and event flow. This model scales the message distribution process while decoupling producers and consumers. Instead of sending messages to different independent channels, applications write a message to one channel that distributes it to when-and-where-required consumers, using message queues as a service. Like message queues, stream-processing systems can either be managed or self-hosted. An internal stream-processing system can be packaged inside the main application or used for enriching the event flow. A managed system frees the

development team from managing servers while delivering high availability and high scalability levels of the stream-processing system out of the box.

4.5. Data Ingestion, Movement, and Integration

Data Ingestion, Movement, and Integration

Distributed Data Systems (DDS) encompass a diverse set of complementary, often overlapping, subsystems for large-scale storage and processing of diverse data, easily combined to create complete solutions well beyond the scope of the components considered individually. Distributed data ingestion enables the incorporation of new information into the system the instant it becomes available. Data streams are a key source, moving information generated by web, IoT, and mobile applications, automated decision-making systems, and sensors and controllers. Such data are stored and processed predominantly in Real-Time Processing frameworks for immediate summary, measurement, and decision support. Batch Processing systems compile a more complete and consistent view of the complete data by ingesting multiple data files concurrently. CRUD actions for existing data are executed at a lower frequency than stream data, resulting in bottlenecks that are accepted to gain the benefits of writing and storing the data in suitable input sizes. Sequence-based sources, such as transaction logs, batch ingestion, and precomputed data summaries are likewise suitable for Batch Processing systems. DDS address not just data ingestion, but also moving, integrating, and preparing it for processing.

Fig 4.3: Data Ingestion, Movement, and Integration

Message Queues and Event Streams make incoming information available with very low latency to interested parties, supporting fast Automation and Easy Decision-Making. A Data Pipeline is an assembly line allowing movement of data from one or more sources through a series of transformations and processing to one or more targets. An Orchestration System schedules and manages the sequence of actions taken in the Data Pipeline. Data Ingestion, Movement, and Integration form a critical part of Data Engineering, often relegated to the role of Data Plumbing, yet no less important than Data Science in ensuring that the right data are available in a usable form for the right processing at the right time.

4.5.1. Message Queues and Event Streams

Message-oriented middleware services enable scalable, decoupled, asynchronous, and reliable communication between loosely coupled components. They are particularly useful for the acquisition and processing of data streams in distributed systems. When consuming, processing, and producing data during their life cycle, components interact with message queues. These transport layers manage message persistence, delivery guarantees, ordering, and scaling. They transmit messages from multiple producers to multiple consumers. Production and consumption occur on parallel and asynchronous channels, enhancing data flow in event-driven architectures.

Event streams implement the same principles and provide ordered sequences of data changes. Event streams present time-bounded segments of newly changed data and enable incremental processing to simplify use cases. The producers of the underlying log mechanism append events in chronological order, and different consumers read those events concurrently. Event streams thus integrate the benefits of log-based storage, serving as a common channel for the data flow between multiple producers and consumers. When queuing components, messages are retained until delivery and removal. But when forming event streams, a component can publish and keep the events or even drop them after consumption. Event streams serve as decoupled and optional storage between systems for requests that do not require strict consistency.

Event streaming systems differ from traditional data retrieval processing. In event-based processing, the focus is on detecting data changes or occurrences rather than subscribing to change notifications. Moreover, freshness is more important than completeness. Event data is transient; anything time-sensitive becomes relevant only for a limited period. When freshness becomes irrelevant, the event can be deleted or archived for historical appraisal. An external system usually provides event data. A message queue or stream manages the data flow, whose producers and consumers operate blindly; the orchestrator deploys them independently."

4.5.2. Data Pipelines and Orchestration

Data rarely resides in a single system. Instead, it is generated, transformed, aggregated, and analyzed across several systems, often multiple times, in order to satisfy various business needs. The process orchestration that enables these workflows must be in close alignment with the technologies and tools used to create, read, and write the data. Organizations process data using different tools and frameworks, each catering to diverse ingestion, processing, and analysis engines. Data pipelines, built using a specialized class of tooling, handle the movement of data between these systems. Data ingestion is a specialized form of data pipeline that acquires data from external producers such as web applications and corporate websites for easy retrieval. It builds a permanent representation in the organization's data storage, allowing for subsequent analysis and hardening of data quality.

An additional category of systems provides orchestration and subtler data movements. Data movement necessitates the execution and management of workflows: the disparate processes and interactions of the different systems must be coordinated to meet the agreed-upon service-level agreements (SLAs). Workflows ensure that subtasks are processed in the correct order, are defined in such a way that they account for possible failures, and correctly determine when the data produced should be consumed. Such coordination is increasingly needed even when using a single data processing technology such as Apache Hadoop, because SLAs can span different processing technologies. The orchestration of the entire data pipeline must be sufficiently versatile to reuse simple data ingestion, integration, and archiving processes. Data integration often relies more on concatenation than joining; planned integration through their use of hot tables, precomputation, and internally driven enterprises minimize the use of integration as a real-time task.

4.6. Consistency, Reliability, and Fault Tolerance

Any distributed sys- tem must address the issues of consistency, reliability, and fault tolerance. Equally, any architecture that provides strong guarantees in these areas will inevitably incur additional costs. The classic CAP theorem, which posits that only two of the three goals (consistency, availability, and partition tolerance) can be achieved simultaneously, is driven by the impossibility of creating a single coherent view of the data when nodes are physically separated. Distributed sys- tems therefore either accept inconsistencies as a normal state of the system, relying on asynchronous communication channels to restore coherence over time, or take an opposite approach, utilizing synchronous communication at the cost of potential availability.

Data replication, the core concept for maintaining consistency and availability, addresses fault tolerance directly. When a write operation occurs, the information is written to additional replicas of the data or state being modified. If one of the replicas cannot receive the data — either because a node is down or because some form of communication failure has occurred — the operation is still able to continue, causing no downtime or external failure. Most open-source distributed databases rely on the Paxos or Raft consensus algorithms, which use multiple replicas to agree on the order of operations in a fault-tolerant manner, preserving a single coherent view of the data. Such distributed systems can only provide strong consistency by storing each piece of information on a quorum on the replicas, thereby requiring at least some of them to be available for read and write operations, and at least one of them to respond in order to be considered reliable.

4.6.1. Replication Strategies

All distributed storage architectures address reliability and fault tolerance by replicating data on multiple servers or data centers. Given the potentially high frequency of data access requests, a simple replication strategy is to replicate the data in a number of nodes equal to n, and to route each request to the first available node. However, the number of replicas necessary for each piece of information is not always equal to n. The higher the number of replicas, the lower the probability for a temporal unavailability of the data, but the higher the cost of updates. The relationship is characterized by a cost function C that increases with the number of replicas and an availability function A that decreases with the number of replicas and is different from the empty set for any finite number of replicas.

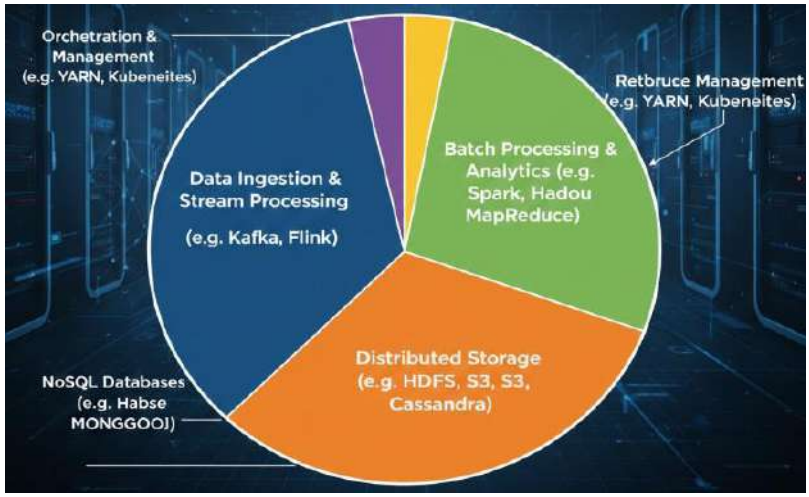

Fig 4.4: Distributed Big Data Processing and Storage Architectures

The operation to replicate data in a distributed environment can be performed in two different ways. One is called eager replication, where the replicas are updated synchronously. The other is known as lazy replication, where the updates occur asynchronously. Eager replication has the advantage of guaranteeing consistency, but suffers from performance degradation when there are many replicas to update on each operation. Lazy replication has the opposite characteristics, with the potential cost of increasing the inconsistency of the system. In practice, the choice between the two types of replication methods is a trade-off between performance of read/write operations and consistency of the replica data.

4.6.2. Checkpointing and Snapshots

In batch processing systems, results of long computations are often written to durable storage for later use. Such results can be stored in the initial data shape, observable by external systems processing incoming late or out-of-order data. Alternatively, results can be persisted in a different shape, providing a materialized view of joined, enriched, or aggregated data. A materialized view with an invalidation time is useful in e-commerce systems for product and customer recommendations. Stream processing systems combine an infinite data source with an arbitrary number of downstream consumers, so computations are frequently interrupted. A strategy for resuming computation is therefore critical to meeting the SLA. Checkpointing takes snapshots of the state at operational intervals, enabling a failure-resume strategy similar to a batch processing system recovering from a node failure. When dedicated resources are available, custom snapshot mechanisms can provide cross-application coordination. Nevertheless, the data ingestion component is the critical exhaustion point in stream processing systems, and Cloudevents provide a formal description of message payload and meta-information.

For events that must be processed strictly in order, message queues can be chained in a producer–consumer configuration. The sequence of events that triggered execution of a downstream consumer is thus inherently available. Additionally, transactional support within and across queue systems prevents fully processed events from being reprocessed.

4.7. Conclusion

The advent of big data constitutes one of the main trends of the information society of the early 21st century, as evidenced by an ever-growing number of published scientific papers, books, and case studies on the theme, an increase in and improved capabilities of big data technologies, a growing interest of information technology companies that make or intend to make such solutions available in the market, and finally, a rise in the amount of information processed. In a step ahead to investigate this phenomenon in

greater depth, this section focused on distributed big data systems' basic functional characteristics, foundations, and architecture. The earlier analysis clearly indicated conceptually distinct data models, distributed storage architectures, execution frameworks, and data ingestion and integration flows. Furthermore, emphasis was placed on how management properties—replication strategies aimed at consistency, reliability, and fault tolerance—strongly shape each layer in acceptable ways. Consequently, the resulting view is easily extensible and provides unified context for formulating solutions to specific problems, thus facilitating the correct choice of paradigms, tools, and techniques.

Cloud computing and big data are two closely intertwined research areas. Cloud computing represents a new delivery model for computing resources, and big data largely considers the set of enabling technologies that allow large volumes of data to be stored, processed, and exploited. Nevertheless, actual infrastructures often fall short of achieving smooth integration between these two concepts. Two aspects are of particular interest. First, it is essential to understand how new big data features can be mined and exploited in cloud platforms.

4.7.1. Future Trends

Distributed Big Data Processing and Storage Architectures. Use an academic, objective tone with clear, evidence-based arguments and formal structure.

Despite their inherently modular nature and elastic scalability, large-scale, distributed systems are progressively moving away from a pure microservice architecture towards a few monolithic solution stacks. Today, few companies dominate the landscape of publicly available processing and storage frameworks, and fewer still actualize real-time processing churning through hundreds of thousands or millions of events per second. The opacity of these behemoths makes it especially important that organizations select their architecture—design decisions regarding data ingestion, movement, storage, and processing—carefully. The blend of available resources and service-specific throughput or latency requirements ultimately determines the degree to which active processes are concentrated on a few frameworks. An immersion in the microservicelike building blocks forming the most common data engineering architectures and pipelines is thus worthwhile.

Availability and durability of data written to these distributed systems are assured via redundancy. Replication of such large volumes of data is an expensive yet effective technique serving demand spikes. Eventual consistency models are largely sufficient and deemed acceptable for many applications, as any long-lived anomalies can be corrected with these systems lacking hard time guarantees. Replication is also often used to reduce

read latencies. A useful optimization of the checkpointing mechanism is the use of snapshots—consistently stored images of a shipping service, usually on unreplicated immutable storage. Eventual consistency can be extended to demand systems with additional complexity while also maintaining data freshness with a slightly stronger guarantee than eventual consistency..

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