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Chapter 3: Data Engineering Strategies for Scalable Enterprise Systems

3.1. Introduction

As enterprises become data-centric, data engineering has emerged as a key IT focus for ensuring that data is smoothly collected, stored, processed, and delivered across systems at scale. Building scalable data pipelines and systems that support a rapidly growing workforce, an increasingly diverse set of data types—both for structured and unstructured data—and a rising set of services that explore and analyze data requires new strategies. Data engineering considers methods, processes, and technologies able to ensure that the needs of business-critical use cases are followed by all of the following data engineering formal practices. Central data lakes help fulfill such needs, but architectural foundations also encompass well-defined layered data approaches aligned with best-of-breed storage systems and data models; data quality management, governance, and certification capabilities; development, deployment, and operational management solutions; and strategic support for cyber-physical systems.

Data scalability techniques now available often derive from core cloud-native concepts. The transparent elasticity of compute resources as needed, without time-consuming intervention and provisioning tasks, is one of the most impactful tendencies for enterprise processes, leading to cloud functions and cloud-run paradigms in the serverless family. The independence from specific cloud providers enabled by multi-cloud and hybrid cloud strategies has become especially attractive for data and analytic processes associated with AI and machine learning. More recent data lakehouse architectures—combining data lake and data warehouse characteristics—also promise to ease the management of cloud data lakes, reduce potential performance problems when serving BI tools via data mart-style filtering, and address the limitations of the data lake paradigm in supporting enterprise functionality.

3.1.1. Background and Significance

The increasing importance of data-driven decision-making and the growing volume and variety of data produced by enterprises have accelerated the adoption of analytical and operational data-driven use cases. Enterprises are exploring new data sources to derive business insights and develop predictive models. Trading firms ingest massive volumes of data from exchanges, news, and social media to gain trading advantages. Retailers aim to counteract shrinking margins by predicting customer sentiment. Ad-tech firms analyze data from countless websites to provide decision-support insights. Yet companies find that, while analytical data are not critical to daily operations, their business may suffer from data unavailability because of data quality issues, poor data management, or unanticipated spikes in user queries. Establishing a robust capability for scalable, reliable, and fast data ingestion across a broad data landscape represents a major challenge.

Data engineering is concerned with building the data-oriented pipelines needed to support analytical and operational data-driven use cases. Data-scaling techniques lift constraints associated with data ingestion and ensure that data-driven insights can be readily consumed. Enterprises tackling these issues benefit from an elemental system architecture that isolates data ingestion and analytical production workloads. Emerging principles for incorporating operational data management complement existing frameworks for data-quality management and enterprise data governance.

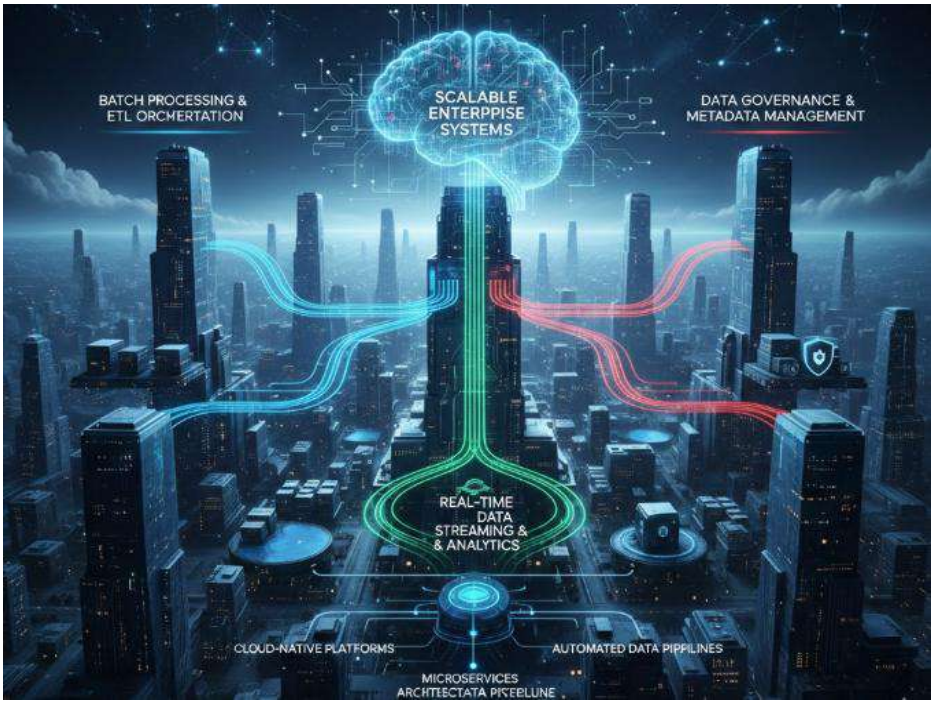

Fig 3.1: Data Engineering Strategies for Scalable Enterprise Systems

3.1.2. Research design

A rapid survey of contemporary practice identifies a comprehensive set of strategies spanning architectural patterns, storage options, data ingestion systems, data quality management, metadata tools, and operational systems. These are examined together in the context of scalability requirements, drawing on experience designing enterprise systems that perform agility and resilience, promote early and optimal use, and free analysts from re-inventing wheels. Four of these techniques are illustrated in detail: an orchestration framework to manage the full dimensional lifecycle from source to warehouse; the duo approach to change data capture for both synchronization and operational users; an elasticity library offering easy access to the elasticity of serverless compute resources; and a cloud-optimized lakehouse architecture that facilitates analysis directly from cloud storage.

Data Engineering (DE) has grown tremendously to fill the gap between Analytics and Operations Engineering. Enterprises are finding that OLAP is neither fast nor flexible enough for exploratory or ad-hoc analysis. Data Engineers respond by providing data pipelines, modelling, integrating, and cleaning data in a Data Lake or Data Warehouse for Analyst self-service. Data Orchestration contains sophisticated tools for scheduling and managing executable workflows that are often both reliable and scale-free. Change Data Capture (CDC) captures changes made to source databases. Data Partitioning, Caching, and Replication move data closer to where it is needed and make it more accessible for queries. The importance of Data Quality and Governance is increasingly recognized, with tools like Data Catalogs and Data Profiling Systems becoming standard in many organizations.

3.2. Architectural Foundations for Scalability

Obtaining good data is hard, but operationalizing it is harder still. Technologies and architectures commonly used in enterprise environments more resemble an interconnected set of nosedives than a cohesive whole. Yet performant, trustworthy, and scalable data products should be a lot more frequent than a platinum record from a local garage band. A layered architecture that cleanly separates storage systems based on data access patterns addresses many of these challenges. Technologies, paradigms, and supporting systems for data ingestion—streaming, bulk, and transactional—figure prominently in implementing large-scale data engineering solutions. Data quality, control, and governance processes ensure that dirty data does not turn a successful enterprise feature into a pain point.

Choose a data first strategy: define and agree on the partitions, schemas, and data quality of the data products of the ingest pipelines and enforce these contracts accordingly. Componentized data orchestration enables an organization to map logical work units to required resources in a consistent and maintainable manner. Supporting operating models and patterns guarantee that the choice of compute should cause concern only when there are good reasons to, while elevating data partitioning, caching, replication, and visible cost control to first-class citizens. Even with these foundations in place, scalability remains a moving goal; options such as elastic compute and serverless paradigms, the arrival of the lakehouse concept, and the increasingly configurable deployment of enterprise systems across multiple clouds or in hybrid on-premises and cloud combinations continue to stretch the horizons of architectural vision.

3.2.1. Layered Data Architecture

A key technique for scaling enterprise systems involves abstracting the data layer into distinct sublayers, mirroring the approach typically recommended for application code. This technique serves to separate flows that typically involve different rates of throughput and velocity, thereby allowing these flows to be optimally scaled. Data mining and machine learning applications typically draw on long-lived and archived data, while operational systems require short-lived and frequently refreshed data. The specific partitioning of an ensemble of data assets is application-dependent, but it is normally several orders of magnitude when considering the largest sets.

The different types of data flows are also appropriate uses for the concept of data-lake storage. Presentation-layer processing generally does not require consideration of how the data is physically stored or prepared for its use, except through the provision of views over the data, and indeed these presentation semantics are commonly a separation of concern that is being rapidly addressed through user-friendly graphical tooling over graphical query languages. The clear separation of data-layer storage from data-layer consumption means that only those applications that specifically require response latency within the sub-second range should ever read data that has not been already materialized for their use. Scaled architecture patterns routinely recommend that only one system-of-record materialization solicitation be active from all users at any point in time.

3.2.2. Storage Systems and Data Models

Data engineering solutions for large-scale enterprise-grade systems can benefit from storage strategies that optimize data storage and retrieval for data processing tasks. While relational databases and data warehouses continue to play central roles in enterprise

architecture, data lakes, and other storage tiers and systems also support these data processing requirements. Leading vendors have recognized these trends and have made empirical data storage models and orchestration services available to customers.

Although current trends favor NoSQL and schema-less data stores, adoption of such technologies introduces specific operational challenges and raises concerns about data quality and reliability. Therefore, some organizations favor a hybrid approach that ensures certain data, especially that needed for critical operations, is stored in highly reliable, structured, and normalised systems, while less critical data is stored in more flexible structures. Relational and time-series databases, data warehouses, and data lakes continue to play crucial roles; the differences lie in configuration, connection method, and provenance. Data ingestion tools take care of schema creation and population of NoSQL stores when the “write once, read many” paradigm applies, while other events require more complex management. Data-ingestion patterns are evolving toward "delivering the right data to the right place at the right time for the right reason".

3.2.3. Data Ingestion and Streaming

The processes of receiving and preparing data for its primary consumers have many parallels with other stages of data management. The operations often involve extracting data from one or more sources and loading it into some persistent store. Input from multiple sources may arrive at different frequencies and at various latencies, and the timing and volume of scheduled ingestion activities can be controlled, to an extent, by process orchestration. Although not a new idea, using change data capture (CDC) techniques to replicate data between systems during ingestion has gained considerable traction in recent years. Streaming patterns are also becoming more prevalent in enterprise data management. The topic is explored in some depth below, covering real-time ingestion, stream processing, and streaming patterns.

Sourcing data and making it available to its intended consumers is a fundamental data management operation. Numerous processes in an enterprise environment depend on such activities, and a variety of data sources are involved. Most sourcing operations can be categorized as batch data ingestion, real-time data ingestion, or stream processing. In these types of operations, the term ingestion encompasses data acquisition, transformation, and loading into one or more persistence layers. Depending on the architecture and the timing and volume of the specific data requests, orchestration may play a role in the scheduling of some ingestion patterns. Database change data capture (CDC) techniques are often used to replicate data between systems, especially when upstream and downstream systems operate in different modes. The demand for streaming data is rising, too: consumption patterns are becoming more real time, sources,

such as the Internet of Things (IOT), produce events with low latency, and businesses require immediate responses to these events.

3.3. Data Quality, Governance, and Certification

Considered a vital data engineering capability in enterprise settings, data quality governance and certification warrant additional discussion. Maintaining data integrity, fitness for purpose, and overall trustworthiness is an important pillar of information systems success. Data quality and integrity hinges on three main pillars: provenance and lineage, metadata management, and data validation and quality control. The specific requirements for and methods applied to each quality aspect depend, of course, on the data's destination and purpose.

Data provenance and lineage usually refer to two closely related but slightly distinct aspects of data origins and transformations. Provenance tracks where input data originated, including collection methods, developers, aggregation, certification status, recommended uses, and so on. Lineage adds details of the operations that the data has undergone. For example, whatever calculation, extrapolation, or assumption has been applied to it since its origin would be included in lineage, and the original sources of those operations would also be a consideration. Both aspects are historically a requirement for sets employed in analytical work or business intelligence reporting; however, not just data scientists and data analysts require, should require, or would find it beneficial to have these details.

3.3.1. Data Provenance and Lineage

The ability to trace the origins of a given data element is a basic form of data governance referred to as data provenance. Data lineage is a more precise term that deals with tracking data in data processing circuits through various transformation processes, irrespective of its origin. These concepts have been implemented by many data warehousing, database, and business intelligence tools. It is also important for enterprise data lakes. Origin or provenance tracking should reveal what generated a given data element, including the source data set, the performing code and execution parameters, and the execution date and time. Traceability of this kind is often demanded by regulations such as SOX, Basel II, and the Health Insurance Portability and Accountability Act (HIPAA).

Transparency becomes even more crucial in data lakes that constitute an enterprise's source of truth. Data validations and certifications usually occur as part of these transformational and migration steps. Detection of errors of any kind becomes of

paramount importance, especially if raw data is used in downstream processing. Traceability should therefore support not only the identification of errors but also their correction. The relevant provenance management systems collect metadata pertaining to the execution of data processes; errors are likely to recur when the trained models are regularly re-executed, which should trigger integrity checks. Testing of upstream datasets can therefore supplement source approval and remain a first line of defense.In enterprise data lakes that serve as a single source of truth, transparency must extend beyond visibility into data contents to encompass the full lineage, quality, and reliability of data flows. Validation and certification processes embedded within transformation and migration pipelines play a critical role in ensuring that data entering the lake is trustworthy and fit for downstream use. Because raw and semi-processed data are often directly consumed by analytics and machine learning workloads, rapid and precise detection of anomalies, inconsistencies, and schema violations becomes essential. Effective traceability mechanisms—supported by provenance management systems that capture detailed metadata about data origins, transformations, and execution contexts—enable organizations not only to pinpoint where errors occur but also to understand how and why they propagate. As models and pipelines are retrained and re-executed over time, recurring errors can surface, making automated integrity checks and continuous monitoring indispensable. In this context, systematic testing of upstream datasets complements formal source approval processes and functions as a proactive first line of defense, preventing flawed data from cascading into critical business decisions.

3.3.2. Metadata Management

Central to the effective use of systems that develop, maintain, and serve enterprise data is an appropriate set of metadata, commonly stored as a data catalog. Most data systems already store some information about the data that they manage. For example, data at rest is usually described by a schema that can be queried in systems such as Hive. Metadata about data in motion is often provided by a message broker, such as Kafka, that tracks part of the schema and the other properties of each stream. However, to be an effective data catalog, the metadata must be extended beyond what is normally maintained and must be complete, accurate, and trusted. The fundamental metadata model for data catalogs typically is defined in three categories: who created the data, why the data was created, and how the data was created. These categories are often divided into subcategories, with the final hierarchy depending on the business needs of the enterprise.

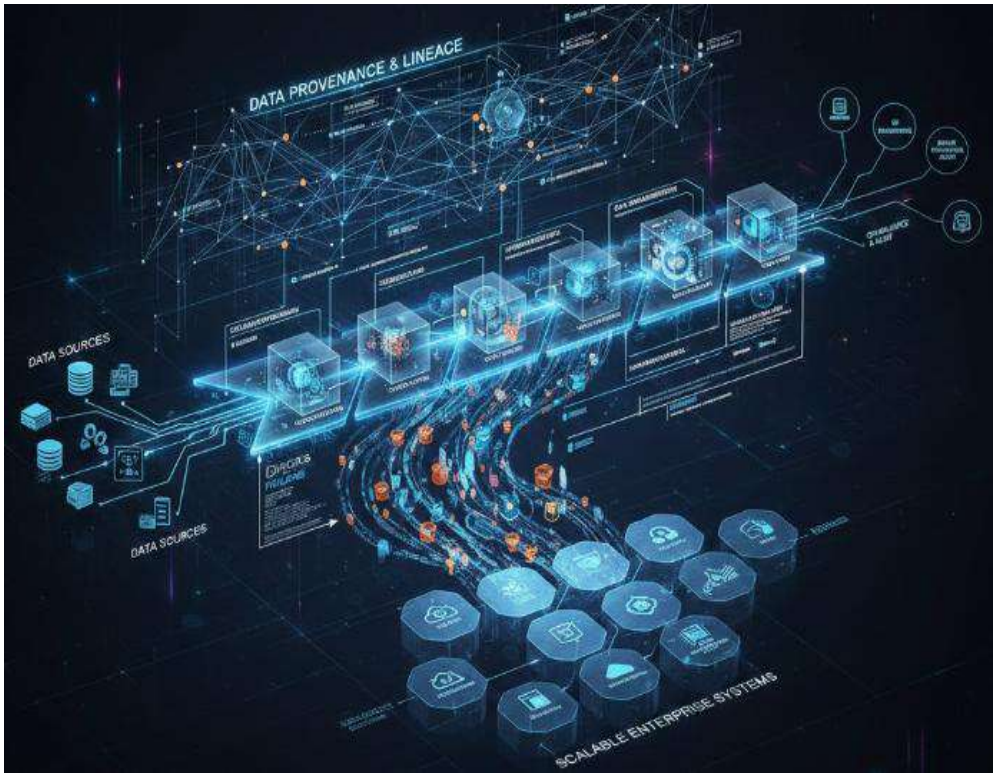

Fig 3.2: Data Provenance and Lineage

Metadata serving systems can be considered external to a data engineering pipeline. They can ingest the additional metadata automatically, such as by crawling. They can also receive metadata recommendations from other tools, such as data quality and data retention enforcement tools. Finally, the effective use of metadata serving systems constitutes a key design pattern in a scalable data engineering system. Metadata management is an overarching capability supported by dedicated systems that provide a centralized view of all the data — and the pipelines that create it — in an enterprise. Catalogs popularized in the open-source community include Amundsen, OpenMetadata, and Metacat. Tools like Atlan and Alation provide enterprise-class capabilities. Note that some data quality platforms also offer metadata management capabilities.

3.3.3. Data Quality and Validation

Reviewing the data quality process might seem unnecessary at first glance, but anyone who has recently been entrenched in a data-engineering project will tell you that data quality resumes are often full of holes. Data engineers are typically the first group in an enterprise to mention data quality, and they pay the price if it's insufficient. Customers of data pipelines, whether warehouses, lakes, lakehouses, or data marts, expect

developers to reduce the risk of bad data moving through these transport functions. Truly good data in a data warehouse seems rare, if not an oxymoron, given the rush toward easy, faster, cheaper Data Fabrics, Data Meshes, and other 10-Stages-for-Night project lists. The advice to test the accuracy of data, both structure and content, has become even more important with the introduction of Code-free ETL and BigQuery (the latter for the Data Analyst "I don't care if it's slow" user) because they are susceptible to providing incorrect data out of the box. Cloud-Geo Data Fabrics, now appearing as the underground-found economy selling antennae, need special-purpose notification functions to signal a faulty Data Quality and Validation.

Traditionally, Tenets-for-testing and Validation Tenets-for-data Quality have been spelled out. These tenets can be mapped to the SQA Data Quality Questionnaire check list—and their closing remarks. Multiple-Choice answers, yet to appear, could easen the testing process: for any task, report the correct option number from a list or check the boxes next to the applicable options. Semantics—the only test passed by test data—is a relative term. Fomula for rings and atonements, by-products of denning and term-project tricks, should be spotted within ten seconds. So, again, who wants to enter a new area of": Query Language?" Lab by Lab, colluding or working in packs of Data Quality-engineers.

3.4. Operational Data Management

A layered data architecture separates the operational and analytics data workloads in a dedicated operational data layer. There are specific requirements for data orchestration workflows in the operational layer: more frequent scheduling, lower SLAs, and support for data changes as well as update and delete transactions. Solutions for Change Data Capture (CDC) of databases and other data sources are available to detect and propagate these changes into the analytics data warehouse.

Operational workloads frequently require the cache of compute-intensive intermediate results. Caching reduces the cost of recomputing these results across successive workloads. Replication, on the other hand, created copies of data in multiple storage locations to support fault tolerance or to minimize the workload on the source of the data. Data replication can also be used to generate a different view of the same data tailored for a specific workload. The distribution of data across shards aims to parallelize the processing of large datasets to improve performance and reduce overall execution time.

With the emergence of Dope (Data Orchestration and Scheduling), an open-source project that integrates hitherto disparate tools concerned with operational data workflows into a common orchestration and scheduling framework. It combines: Airflow for

workflow orchestration; OpenLineage to capture data provenance; Great Expectations for data quality checks; and DBT for transformations of the operational data layer. Dope fulfills an acute need in the operational business analytics community by applying analytics concepts usually reserved for the analytics environment to the complete business analytical lifecycle.

3.4.1. Dope: Data Orchestration and Scheduling

Data orchestration enables collaborative flows involving data transformation and exchange between systems, applications, and products. A recent implementation of a pioneering internal orchestration solution named Dope (Data Orchestration and Pipeline Execution) within a telecommunications enterprise illustrates typical considerations.

Dope integrates package management, task orchestration, and data-transfer logic across multiple generations of analytical products, ensuring a consistent, governed approach for all stakeholders while encouraging code reuse and contributing to data certification upstream. The orchestration tool captures lineage information from upstream products and sources and includes a status layer for production-quality certifications. Parallelized task orchestration with an intuitive Gantt-style interface is complemented by staged integration scripts that ensure the correct package version and related requirements are available throughout the connected environment. External scripts for ETL, ELT, data migration, and other functions call on the orchestrator via a simple webhook REST integration. The orchestration solution incorporates native data-transfer functionality to automatically move data into a connected environment.

An enterprise accelerating procedures for information transfer and transformation between data marts, lakes, operational systems, applications, and other data-driven investments has taken an important step in implementing an orchestration solution. Dope (Data Orchestration and Pipeline Execution) performs package management, task orchestration, and native data-transfer logic across multiple generations of analytical products, ensuring a consistent, governed approach for all stakeholders while encouraging code reuse and contributing to data certification upstream.

3.4.2. Change Data Capture and Synchronization

Given the volume, variety, and velocity of data created within enterprise environments, it is impractical to rely on batch processes that read entire datasets from source systems for processing, changes made since the last read must instead be tracked and used to incrementally adjust these datasets.

A change-data-capture (CDC) approach is often employed to detect and capture transactions reflecting insertions, updates, and deletions in transactional databases, allowing only changes to succeeding, dependent datasets, thereby reducing latency and upstream propagation time. However, CDC management presents important issues, including how to implement it effectively and efficiently at scale—across heterogeneous data—how to meet the processing needs of downstream systems, and how to ensure that they reflect a consistent, coherent state of the data at all times.

Solutions to these issues include Transactional Data Management Systems (TDMS) that act as central Transaction Log Management Systems (TLMS) that support multiple replication clients by tracking changes at the transaction level. Signals from the TLMS can also be used by other components of data orchestration and scheduling systems, such as Dope, to effectively trigger data-processing jobs at processing engines.

Beyond operational Delta Manage and CDC capabilities, synchronization strategies are required to ensure that all data systems remain aligned with each other, even if their physical sources are removed or bypassed. Products are available that scan for data differences, presenting holistic results, enabling users to modify source or target systems accordingly, and, if necessary, automatically performing the changes on a dataset. These systems help support multi-cloud and hybrid data architectures, ensuring that all datasets are operating in sync in all environments and cloud platforms.

3.4.3. Data Partitioning, Caching, and Replication

Effective partitioning of data in scale-out and big-data systems is of paramount concern, owing to the volume, velocity, variety, and veracity of the associated workloads. In these settings, partitioning focuses predominantly on horizontal data partitioning with partitioned tables to achieve a diagonal smearing of data across compute nodes. Appropriately determined row partition keys serve to optimally localise processing workloads to a minimum number of nodes for reasons of data transfer latency, network bandwidth, and reduction of I/O overheads. In contrast to vertical partitioning, which is widely used in traditional online transaction processing (OLTP) systems, where the data in each column is stored as a separate table and indexed, vertical partitioning in scale-out systems is an approach of last resort as it reduces the parallelism of processing by requiring more data partitions to be processed and is one of the key factors that affect performance quality.

Caching is a key performance optimisation that is typically employed when TP workloads write small transactions that subsequently read back the newly written data. In these circumstances, the data being read is stored, or cached, in memory, allowing read back from memory rather than from disk or flash. The aim is to avoid the high cost

associated with combined disk I/O and network round-trip time (RTT). Caching can also address the frequently encountered scenario in both multi-tenanted environments and systems with many related but distinct datasets of reading small related datasets with high frequency. In such cases, when the datasets are cached optimally, the time to read them reduces to that required to read a single large dataset.

Replication is another commonly used performance optimisation that is employed in multi-tenanted systems. For both TP and BI workloads, the often frequent nature of reads of low cardinality categorical columns, particularly by relatively distant or remote distributed sites, makes these columns prime candidates for replication and caching. In BI workloads, numerous queries will scan the same replication of the same dataset, sometimes even simultaneously.

3.5. Scalability Techniques in Practice

Elastic compute capabilities are necessary for growing workloads. They decouple hardware provisioning from workflow execution, allowing capacity to momentarily exceed deployment resources and supporting cost-effective caretaking. Serverless execution environments—often blending IaaS, PaaS, and FaaS—are attempting to simplify workflow development, debug, and monitoring even further.

Fig 3.3: Scalability Techniques in Practice

Cloud data lakes converge cloud storage functionality with data model support tailored for large-scale batch analytics. Lakehouse concepts enhance cloud data lakes to additionally support BI workloads and provide a data layer on top of cloud object storage. They merge data warehouse capabilities into the data lake, enabling a more

unified experience. Cloud object storage has high performance, almost limitless scale, commands low storage costs, and achieves higher availability for long-term data storage compared to HDFS-based storage solutions. Data lake, lakehouse, and extent-parquet storage concepts support more efficient and performant data creation and consumption while optimizing storage costs.

Data management in hybrid or multi-cloud scenarios is often driven by requirements for sovereignty, latency, cost, or avoiding lock-in. Multi-cloud solutions are often architected and operated by manuals to present a unified. Hybrid cloud extensions are often achieved simply by having data backup, archiving, or DR solutions operated by the vendor externally managing on-premises and cloud data center installations. Additionally, the evolution of IoT and AI trend is driving new paradigms: edge-computing architectures connect the endpoints of cloud computing.

3.5.1. Elastic Compute and Serverless Paradigms

Elastic compute and serverless paradigms are powerful principles that lower costs related to workload provisioning by allowing resources to be allocated on-demand, as needed during the execution of workloads. These principles have existed for many years in the context of Infrastructure as a Service (IaaS), with clouds providing virtual machines that can be efficiently started, powered off, and removed based on demand.

These principles have gained attention in the context of Data Engineering by enabling flexible provisioning of compute as close to the data as possible to minimize egress costs and that, even more importantly, provide fine-grained scaled provisioned resources, where a user requests resources on demand and pays for usage by the second or millisecond. These ideas were present—in a different form—decades ago in MapReduce with its master/slave architecture, where worker nodes running as needed on clusters composed of commodity virtual machines or bare metal. Other paradigms such as Apache Hadoop on-demand clusters and Apache Presto executor clusters provided similar capabilities. What makes the current iterations different is an increasing focus on the user experience and hiding as much as possible the management overhead while providing a much larger ecosystem of workloads in combination with simpler pricing models.

3.5.2. Data Lakehouse Concepts

The lake-warehouse architecture combines elements from both the data lake and data warehouse approaches into a single end-to-end data platform, enabling the management of analytic and operational workloads on a common storage. A unified data serving layer

is achieved by using a structure-storage format with tape-like object storage supporting automated parallel data processing. The lake-warehouse architecture supports both batch and streaming data ingestion, enabling scalable and modular event-driven ingestion pipelines. The storage system delivers ACID transactions and schema enforcement to support concurrent batch and stream accessibility with strong consistency.

The lake-warehouse architecture has attracted the interest of several major cloud providers and cloud-based analytic ecosystem vendors. Azure Synapse Analytics and Google BigQuery support lake-warehouse concepts and are part of their respective analytics ecosystems. Snowflake offers similar functionality and can be effectively combined with other lake-warehouse ecosystems, including Apache Spark and Databricks. A comprehensive lake-warehouse ecosystem is created through the integration of the products from Databricks, MongoDB, Tableau, and Delta Lake. Following the lake-warehouse design principle, Delta Lake replaced the Hive Metastore with its own storage layout and schema.

3.5.3. Multi-Cloud and Hybrid Architectures

Multi-cloud deployments, combining services from multiple suppliers, have become increasingly common in enterprise environments. Enterprises choose multi-cloud to combine and optimize individual vendor service offerings, avoid cloud lock-in, use cloud resources deployed in separate operational jurisdictions, and comply with legal and regulatory requirements. Hybrid architectures, integrating on-premises and cloud resources, are often used for sensitive data in regulated industries. Both architectural patterns increase the complexity of data engineering operations. Data movement and synchronization across multiple cloud vendors must be managed, and the reconciliation of different identity, monitoring, logging, and alerting mechanisms in different clouds requires careful planning.

Cloud service providers are investing heavily in data engineering capabilities. Many providers offer services for storage certification, data quality checking and validation, monitoring of data movement and pipelines, and data governance. Some of these services tend to be limited in functionality. Third-party vendor offerings, including those of enterprise software companies and specialist data management vendors, are rapidly evolving to fill these gaps.

3.6. Conclusion

As enterprises continue their quest for scalability, the aforementioned foundations and guidance can foster more efficient data engineering systems, thus maintaining a

competitive edge. Several scalable data engineering techniques are also maturing and emerging. The elastic compute paradigm allows compute resources, such as VM and container clusters, to be deployed as needed to match data processing requirements. Serverless computing extends this concept, building scale hides completely from data engineers. Data lakehouses, combining the best features of data lakes and data warehouses, perform well for modern multi-source analytics and BI use cases. Multi-cloud and hybrid cloud architectures distribute data services across more than one public cloud provider or combine private and public clouds, enabling the control of sensitive data, avoiding vendor dependence, and optimizing cost and performance.

During the next years, rapid developments in the field promise intelligent data engineering to alleviate the increasing complexity and effort of data engineering systems in the cloud era and the new AI wash of data science systems, i.e., the introduction of "AI-scientists" powered by new (large) models capable of synthesizing complex information from unstructured and heterogeneous data boom, making it feasible to deploy complicated enterprise systems exploiting such information without requiring a big team of expensive experts. Use of Semantic Knowledge Representation and Ontologies is another emerging direction to alleviate the complexity of enterprise data analysis by providing a domain-centered conceptual base for machine learning, data analysis, and software engineering.

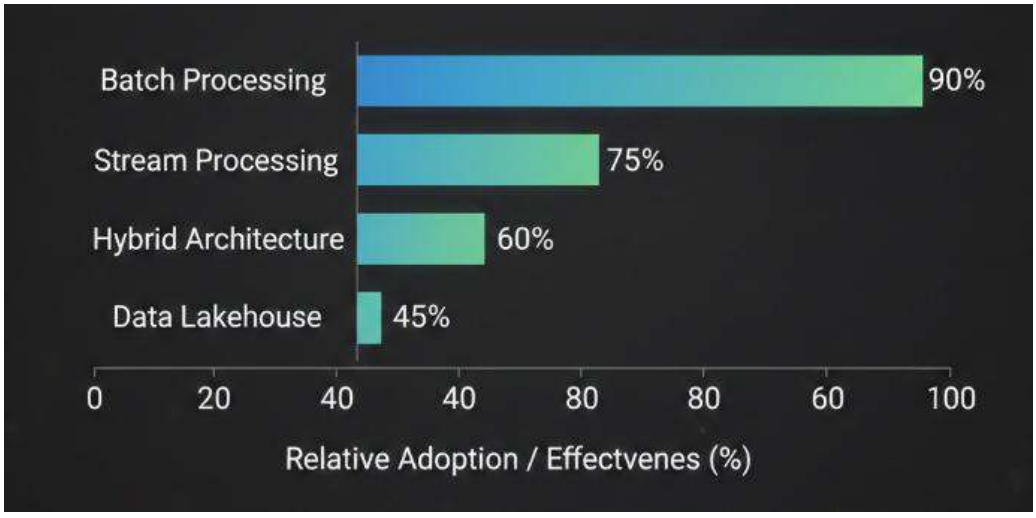

Fig 3.4: Data Engineering Strategies for Scalable Enterprise Systems

3.6.1. Emerging Trends

Developing data infrastructure that scales with growing business demand is a strategic priority for many enterprises. Scalable architecture relies on appropriate separation of

concerns between logical and physical design layers. Logical concerns are captured in a layered data architecture composed of data ingestions, storage, quality management, governance, and operational management layers. Physical needs are best addressed with NoSQL storage systems based on document, graph, time-series, or column-store data models, and capable of ingesting, managing, and delivering data as a streaming flow. Achieving architecture scalability requires a collection of composite and related techniques.

A complementary set of techniques is used to develop data infrastructure that elastically scales to fulfil fluctuations in business demand. These techniques embrace elastic and serverless paradigms for operational compute workloads, the lakehouse concept for analytics workloads, and multi-cloud or hybrid deployments capable of distributing workloads for cost-effectiveness or data locality. These techniques are rapidly being adopted by large enterprises, implementation has been corroborated through enterprise experience and case studies of leading service providers, and detailed definitions of key concepts can be found in industry and standards literature..

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