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# Chapter 3: Data Engineering and Scalable Analytics Pipelines

## 3.1. Introduction

Data engineering underpins the design of scalable analytics pipelines, yet most books, courses, and tutorials on data engineering ignore essential foundational topics. An appreciation of these topics enhances proficiency in data engineering, improves the quality of deployed pipelines, and enables engineers to avoid implementing common data problems. A detailed overview is provided of fundamental concepts in data engineering—not explanations of the internals of a cloud provider, the machine-learning pipeline, a specific tool, or a programming framework—but topics that every data engineer should know about, regardless of how they are assigned the title.

Some solutions to these problems are also proposed, based on foundational concepts in data engineering. At a high level, data engineering is about building scalable analytics pipelines that meet business requirements. The analytics pipeline encompasses data acquisition, ETL, data modeling, and the consumption of data by data science, business intelligence, and operational teams for analysis, reporting, and operational decision-making. The pipeline is usually orchestrated with a high-level tools like Apache NiFi or AWS Glue. The emphasis on scalability arises from the reality that data pipelines and the associated analytics are often processing large volumes and varieties of data. Additionally, the solutions are specific to the fundamental concepts in data engineering enumerated next: data modeling and storage; ingestion, cleansing, and validation; architectural patterns for scalability; data processing frameworks and tools; data quality; and orchestration and scheduling.

### 3.1.1. Overview of Data Engineering Fundamentals

Data Engineering is the design, construction, management, and orchestration of scalable data pipelines. It encompasses the end-to-end processes powering analytics on large

datasets, from data ingestion through its arrival in a persistent store, cleansing, transformation, and quality verification, to loading into a data warehouse for analytics consumption or provision to machine learning instrumentalities. The theme has assumed greater importance with the advent of big data, necessitating systems capable of processing large volumes of complex data safely and reliably. The flow-through paradigm identified by Babbitt in 1952 provided an initial plot blueprint. Today, big data applications tend to incorporate multiple sources of continuously flowing data alongside batch processing modes, leading to designs such as the Lambda pattern.

Data Engineering, like Software Engineering, Computer Science, and Data Science, varies with context. Data Engineering may be distinguished from similar terms by its focus on scalable data pipelines, the end-to-end building of data flow systems that meet the requirements of these pipelines, and by the concurrent demands of Data Science and Data Analytics for scalable, efficient, and easily accessible data flow processes. Data pipelines are designed for a single purpose in mind, are used as backend capabilities for defined users or customers, and normally cater for a data-set that is not used by others.

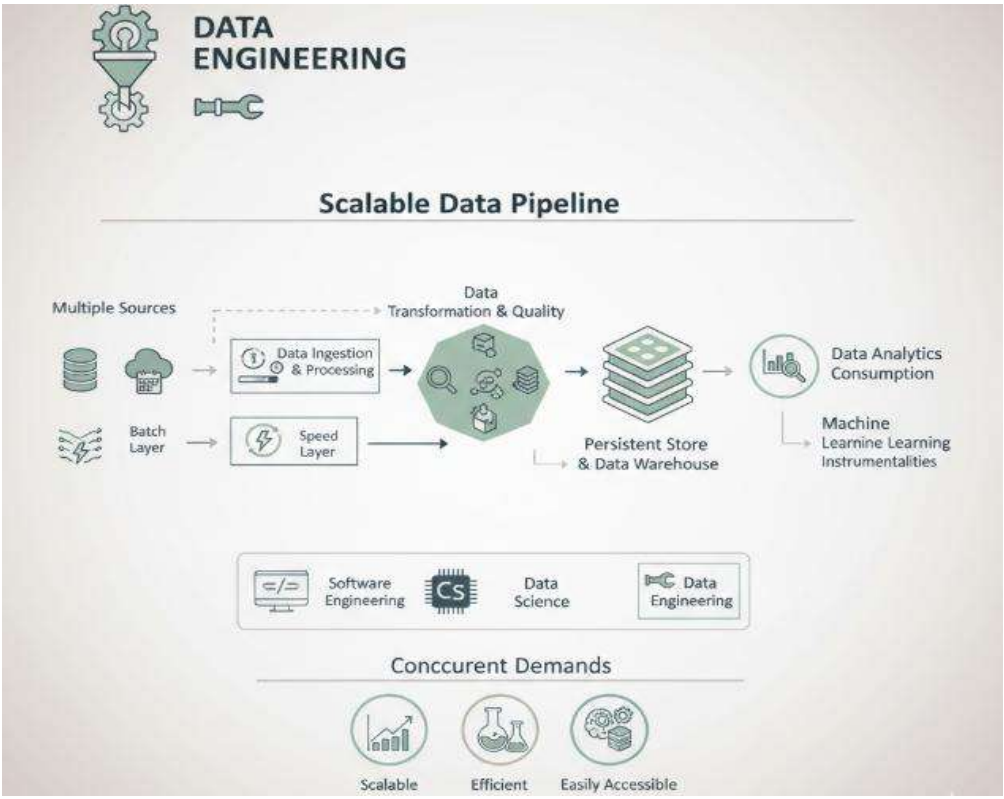


**Fig 3.1:** Orchestrating the Flow: Principles of Scalable Data Engineering and Pipeline Architecture

## 3.2. Fundamental Concepts in Data Engineering

Finally, data engineering processes are rendered practically helpful and useful in data analysis by making the 4Vs characteristic of the data more manageable. Proper data modeling and storage are essential in addressing issues of volume, variety, and velocity; batch or streaming data architectures support the processing and delivery of data with acceptable a speed and timeliness, and data engineering systems like LinkedIn's Kappa architecture allow organizations to explicitly impose temporal constraints on the quality of insights gleaned from their data. Similarly, Provenance captures the lineage of data as they traverse multiple transformations from source to destined consumer, thus consolidating efforts made on avoiding 'yet another' reference data to help avoid duplication.

Data Modeling and Storage Paradigms

Data models aim to provide a logical description of the data and their relationships without reflecting the details of physical storage. Similarly, storage paradigms concern the physical representation of data in a way suited to producing the desired analysis or providing the required feature present in most features. Natural, multidimensional or spatio-temporal data can be represented and stored in a relational format. However, expression of schemas or operations in a language that incorporates the specialized functions of these data and making a modelling schema that consists of sample data and coordinates of the data will be less complex and require hence less time and resources.

### 3.2.1. Data Modeling and Storage paradigms

Data storage lies at the core of all analytic solutions. Regardless of upstream data sources or downstream algorithms, data must be stored at least temporarily and typically durably somewhere along the pipeline. Thus, the choice of data model and storage system, along with granularity, integrity, and performance of the data, is critical. When taking an architectural perspective, two main concepts come at play: the data model and the storage technology. Data can be organized in a formal schema, often representing a subset of a relational model or according to a less formalized structure to support faster ingestion. Finally, depending on usage patterns, data can be stored in memory, on solid state disks, or on spinning disks, according to application business requirements.

The chosen data model must reflect how each data element will be used in the investment processes. From an analytical perspective, data can often be structured hierarchically, enabling an intuitive use case definition. However, this normal form is not always possible due to the inherent structure of the source data or because the data will be queried along unexpected paths. Data, as in the star schema design philosophy, must therefore be stored at the grain that best supports access patterns while minimizing

redundancy for load performance. Redundance is natively supported in denormalized formats, such as NoSQL databases and messaging queues, which, in fact, adopt a "schema on read" philosophy. In scenarios in which very different consumers access the same data set – for example, when running exploratory analyses dipping into internet-scraping data – denormalized layouts may be a good option.

### 3.2.2. Data Ingestion, Cleansing, and Validation

The first stage of analytics pipelines involves getting data into a system for storage and processing. Data ingestion can range from simplistic batch loading tasks, performed every few hours or days, to near-real-time streaming connections feeding data lakes—typical for Internet of Things or social media applications. Regardless of how or how often data is acquired, any data engineering pipeline should include processes for data cleansing and validation. These operations help ensure that the data being loaded into the storage layer for future analysis is of sufficient integrity to support the querying, reporting, and predictive modeling needs of data consumers.

Cleansing operations can usually be automated. For example, duplicate records can be detected and removed as they are being ingested through a dedicated heavy-write landing table. Such a cleansing task is often automated during the early stages of developing a data pipeline, but the rules guiding the operation should evolve to support changing data usage patterns. With increasing use in production, new deduplication techniques might be needed, such as using Change Data Capture delta files from the source system. Whereas cleansing focuses on maintaining a clean state in the destination store, validation ensures that the data being ingested conforms to expected structures and distributions.

## 3.3. Architectural Patterns for Scalability

The analyses explore three of the most widely adopted architectural patterns examined in relation to scalability: Batch versus Streaming architectures, Lambda and Kappa architectures, and a variety of Evolutionary architectures.

Batch versus Streaming Architecture

Batch architectures are designed for processing large volumes of available data with a certain latency; this latency is acceptable because the insights gained must form the basis for subsequent business actions that will occur much later. These Batch architectures typically rely on scaling up IT resources to handle higher volume processing largely achieved using Distributed Processing methods. Powering modern businesses with minimum latency often results in a new set of requirements that Batch architectures can

no longer satisfy. Data and knowledge are constantly evolving, affecting the quality and accuracy of the insights and business actions derived from such architectures. Consequently, the insights generated in Batch campaigns can be regarded as second-hand knowledge upon which business decisions have few opportunities to react and adapt swiftly. Streaming architectures satisfy a different set of requirements by processing data on-the-fly while it is being created or ingested. Such architectures are designed for supporting near real-time engagement where data is captured and processed in very small micro-batches and subsequently made available for immediate exploratory analysis. In addition to these two polarity extremes, Hybrid architectures are also commonly adopted, where a subset of the data is processed in near real-time while the rest is gathered and processed in Batch mode.

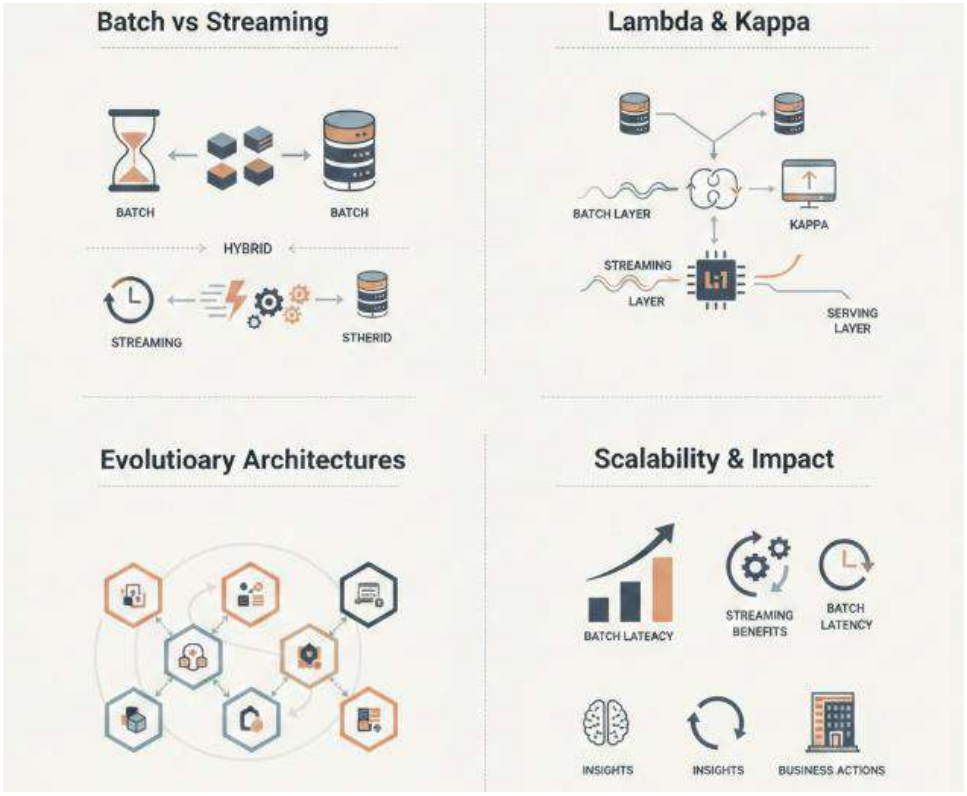


**Fig 3.2:** Architectural Divergence in Data Scalability: A Comparative Framework of Batch-Stream Correspondence and Evolutionary Systems

Lambda and Kappa Architectures

Lambda architectures are famous for unifying Batch and Streaming architectural patterns. Such architectures are conceived primarily to encompass the Stream–Batch correspondence by employing more involved layering designs and by transferring state information from Batch to Streaming. In the Lambda design, the Batch and Streaming

processing subsystems are characterized by a Shared Information Store that contains the knowledge generated from the Batch processing subsystem. This Shared Information Store is exploited in two locations: by the Serving Layer that exposes the knowledge thus far gained, and by the Speed Layer that applies sampling-based techniques on the new data of the Streaming Processing subsystem. Although the Lambda architecture has been adopted by large companies, it is not without its drawbacks and challenges. The Kappa architecture acknowledges the shortcomings of the Lambda design by primarily focusing on the Streaming subsystem and leveraging the Streaming data for the Batch processing as opposed to the reverse. Such a model, however, only considers the Stream side of the Stream–Batch correspondence and hence remains directed solely to those applications for which such a direction suits best.

### 3.3.1. Batch vs. Streaming Data Architectures

When designing and implementing storage schema, data engineers must consider how data is stored and made accessible to the various analytical workloads dependent on it, as well as how it flows from its originating system and transforms into a format suitable for the destination workloads. These considerations ultimately determine the batch or streaming nature of the pipeline. Whether sending large CSV files daily for downstream processing or implementing a network appliance that ingests continuous video frames, designers are faced with the challenge of supporting the lifecycle of the data without jeopardizing the performance of data workflows.

A stream architecture, defined as the processing of input data in a continuous fashion, creates data at an unprecedented rate. While streams appear unbounded from the outside, internal systems break the flow into manageable chunks, such as a set time interval (e.g., micro-batching) or a fixed size (e.g., number of messages in a buffer). These small batches are processed at a faster rate than their generation in an effort to provide near real-time results. The latency requirements of these Near Real-Time (NRT) workloads necessitate the upstream loading of already ingested and processed data to ensure its availability for processing before reaching the destination. Systems that process unbounded data usually write results to either another data stream consumed by an NRT workload or to offline storage available to other architectural patterns.

Batch data architectures process historical data at a much slower rate — typically at regular intervals that can be hours or even days apart. Batch systems accumulate large volumes of data that make their processing externally visible only when the volumes surpass a certain threshold. These suboptimal latencies for modern applications have driven the migration toward hybrid-streaming pipelines and real-time stream architectures, relegating batch systems to historical analysis, compliance reports, and predictive modeling.

### 3.3.2. Lambda, Kappa, and Beyond

Scalability is crucial for an analytics pipeline, and several architectural patterns have emerged to address it. Lambda and Kappa architectures facilitate batch and streaming processing respectively, while recent evolutions of streaming frameworks seek to further collapse the complex systems that Lambda necessitates.

Many Big Data applications fall into the Lambda architectural pattern. From a data-storage perspective, raw data is stage-managed in a colorless repository (sometimes called a landing zone) before an analytical zone is populated from the raw data. Traditionally the analytical zone is a data warehouse populated by a cluster of Batch Workers and an OLAP engine. However, new initiatives like Apache Druid, ClickHouse, and Iceberg are heavily optimizing big-columnar-database-OLAP hybrid queries and can also directly serve the analytics community. Nevertheless, it still remains necessary to maintain a copy in a format that supports a full analytic workload. This provides a second pathway for data dissemination: directly from the landing zone in a colorless form to zones that serve external needs, most commonly as Data Marts or Data Lakes.

This dual-path approach brings complexity both in terms of orchestration and in terms of data consistency. Particularly in complex environments that are evolving toward the new paradigm of releasing daily scorecards and news broadcasts, as well as operating within a complex event environment, Batch Workers are required to handle complex dependencies across Data Marts and across levels in multiple Data Lakes. These increased dependencies, the need to support both near-real-time and longer-term information, and obviously the need to scale beyond a single Data Mart are the key drivers of the second architectural segregate-assign-aggregate-and-distribute pattern for analytic Data Marts and Data Lakes.

## 3.4. Data Processing Frameworks and Tools

The end-to-end orchestration of data pipelines, the reliability of the appliances used and in particular their capacity to operate at scale all hinge upon an efficient design and implementation of the software that processes data along the journey from ingestion to final analytics. A software development perspective is therefore key to a successful deployment, from the choice of processing framework to the language and runtime in which the transformation scripts are implemented.

The requirement for a processing framework capable of scaling compute capacity on demand can rarely be waived, and is justified by the increasing portion of analytics in streaming form. Indeed the data growth potential of large organizations has already led solution architects to consider both Lambda and Kappa architectures, or variations

thereof, as natural design patterns for data-intensive businesses. At the same time, the desire of SME to embrace analytics is definitively beyond the technical complexity that a Lambda architecture introduces, and these organizations may naturally focus on a simpler batch processing architecture. Regardless of the underlying architecture, the horizontal scalability and user-friendliness that frameworks such as the Hadoop Distributed File System (HDFS), Apache Hadoop or Apache Spark DataFrame API offer has become a de facto requirement for large analytics workloads.

### 3.4.1. Distributed Computing Fundamentals

A traditional system for the execution of a single-purpose, non-distributed, and sequential workload runs on a simple model of computation, consisting of a sequence of operations to process data retrieved by the dataset from a local store. Data engineering systems enable the execution of multiple different workloads, with no constraint on execution order, and that can also be specified and scheduled by different users. Moreover, source and sink datasets may reside in different locations and among big data workloads can in principle change location. The execution of such a workload is carried out on a cluster of machines, with each job being executed on a dynamically assigned set made up of the data nodes for the source dataset, and with each operation alternatively reading from and writing to intermediate datasets.

The implementation of data engineering systems is built upon three fundamental paradigms: data parallelism, distributed programming, and data flow. The first one employs distributed execution to process large amounts of data, but each processing operation still has to run sequentially on a single node. The second one captures the distribution of data and the dynamics of workload execution. Finally, the data flow paradigm leverages the data parallelism on individual-loaded operations to abstract their distributed execution. These three paradigms are encapsulated within a data processing framework, which defines the main building blocks and patterns for the development of distributed data transformation algorithms and wraps the technical details of the execution with higher-level entities, procedures, and tools allowing data engineering users to focus on the task and avoid the intricacies of parallelism when appropriate.

### 3.4.2. Modern Frameworks and Engines



Numerous frameworks and engines have appeared in recent years to address general-purpose analytics workloads, in many cases inspired by the MapReduce paradigm. Key characteristics of these frameworks include a focus on easy cluster setup for large-scale

data processing, improved asynchronous I/O, and fault tolerance through checkpointing. A consequence of these characteristics is that Cloud computing environments such as Amazon Web Services (AWS) and Microsoft Azure have gained popularity for data analytics workloads.

Apache Hadoop is an open-source implementation of MapReduce and the Hadoop Distributed File System (HDFS) designed for high-throughput batch processing of very large datasets in clusters of inexpensive commodity hardware. Scalability is achieved through data partitioning, replication, and performance isolation. The Hadoop ecosystem consists of a wide variety of tools, libraries, and daemons to support not only MapReduce query execution, but also data ingestion and preparation, data quality and governance, scheduling, and serving. Hadoop is the de facto standard for large-scale analytics in many organizations. It is also supported by the Business Intelligence (BI) tools from all major vendors.

## 3.5. Data Quality, Provenance, and Governance

Data-dependent applications are only as good as the data they consume. Putting the data into these pipelines, cataloging metadata, checking data quality, recording history, and factoring in end-user governance become key engineering tasks, received less attention in prior generations of data analysis than they deserved. The projects demonstrating failure of best science practices showed that bugs and misunderstandings in the data extracting, transforming, and loading process also took their toll. Addressing these concerns properly goes a long way toward ensuring that the results are convincing, reproducible, and respected.

Data quality assurance includes assessments to check for both the reasonableness of the data and the degree to which the results satisfy the intended use of the data. Data cleansing processes can be developed alongside those assessments. Data provenance serves as the information backbone at this layer, recording how input data were prepared and enabling the exploration of data quality problems and appropriate remediation. It also provides lineage from sources to products, supporting auditing compliance. Provenance thus simplifies the work of any analysts who need to credibly understand how or when the data changed in order to certify the analyses they perform or the products they publish.

### 3.5.1. Quality Assurance in Pipelines

Data quality is central to the success of Analytics and Machine Learning applications. However, quality management requires a rigorous and structured approach. Specifically,

the quality of a Data Product relies on establishing and monitoring Service Level Objectives (SLOs) for its core data set. Business stakeholders must concur on the importance of each SLO. Unrealistic SLOs, designed to keep any wrinkle from affecting the results of an Analytics or Machine Learning task, create two problems. They instil a false sense of confidence in the overall Data Product. Simultaneous breaches of unrealistic SLOs, while not impossible, are extremely unlikely. Such breaches warrant immediate attention, but are invariably accompanied by resolvable, if temporary, problems elsewhere in the Data Product.

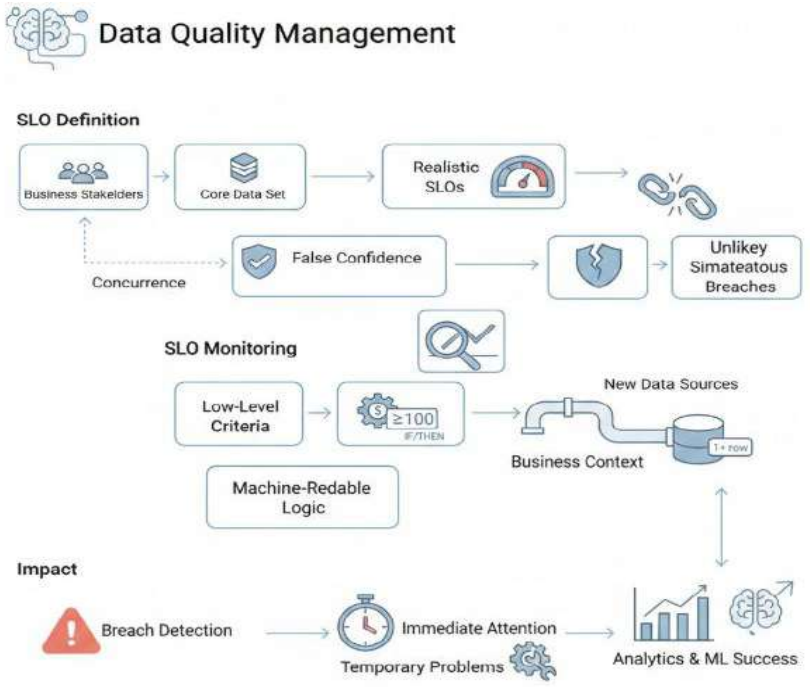


**Fig 3.3:** Optimizing Data Product Reliability: A Framework for Stakeholder-Driven Service Level Objectives in Machine Learning Pipelines

Business stakeholders must approve the candidates for monitoring. Since even basic SLOs require a clear explanation — for example, just what is an ‘active user’? — low-level criteria, such as threshold boundaries for distinct count, should be artificially simple but conceptually meaningful. Initial values also need sufficient business context to avoid accidental breaches. When service operations require pipelines to be extended to new data sources, their original SLOs should be complemented by simple SLOs for those sources, such as ‘at least 1 row since the last Data Quality check’. Logic that detects a failed join, for instance, may not be provable formally, yet it should be machine-readable and employed.

### 3.5.2. Lineage, Auditing, and Compliance

Data provenance, as a discipline, is concerned with the chronological documentation of events related to a dataset. Examples of some core questions relevant to provenance are the origin of a dataset and the steps involved in its creation. A data-management decision often involves the consideration of multiple KPIs from multiple sources. Business-intelligence systems typically function in tandem with "operational dashboards". Which set of controls is governing the scheduling overrides and capacity control? Who constructed the models supporting the investment recommendations? What parameters controlled the batch-orchestration decision? What research group adopted a deviance-based analysis of annual general-meeting oral reports?

The answers to these questions facilitate auditing and compliance efforts, such as regulatory checks. For instance, the provenance of a data feed for a SAS risk system should (and probably must) answer: What trading desk generated the feed? Does the risk system control the batching of data for the User Behavioural Database? Who evaluated, tested, and accepted the quality of the input ngrams and anchors for the Auto Suggest engine? What were the relevant parameters? With the increasing frequency of regulations requiring boarding pass designating, ensuring the correct data provenance of data is critical.

## 3.6. Orchestration, Scheduling, and Reliability

Workflow orchestration coordinates the execution of diverse interdependent tasks, and one of the most common orchestration patterns in data pipelining involves using a batching scheduling system to trigger the subsequent tasks. Batch schedulers periodically scan a configuration file, and when particular tasks finish, they often trigger the execution of dependent tasks that have not yet completed. This dependency detection can be further enhanced by an ad hoc mechanism that tracks the status of tasks registered with a key-value store.

Idempotent restart mechanisms, retry logic, and observability support go a long way toward making most drivers and other analysts the envy of the ops team. When executing workflows that are composed of flows in a spatial sequence, providing such support can sometimes be a burdensome and tedious resource drain. Each flow must be explicitly coded. Miscommunication may cause some flows to not conform to the original retryable intent due to rapid fire triggers, or appear to be running concurrently when only of them can execute at a time.

Always test functions and transformations in isolation against representative data before connecting them together with pipeline machinery. Ensure that data generated is of good

structure, layout, and content. When testing more complex functions, include at least one failure mode.

### 3.6.1. Workflow Orchestration Patterns

In many cases, reliable processes consist of a series of discrete phases that together generate the end product. Examples include machine learning pipelines, report generation for reporting or analytics, and dashboard refresh operations. Each segment can itself resemble a full data pipeline, operating in batch or streaming mode. Although it is possible to schedule these processes as independent operations, using an orchestration framework simplifies their construction and maintenance.

Workflow orchestration frameworks typically define workflows using a domain-specific language (DSL) or a general-purpose programming language. The components of the workflow are defined as procedures or functions that declare their input and output datasets or tables. Specific operations such as copying files to S3, invoking an external API, or training a machine learning model may be invoked using a library that provides wrappers to common functions. Workflows can also be defined as directed acyclic graphs (DAGs), which define dependencies between operations but ignore more complicated properties such as cadence and concurrency. Users must also define a target scheduler or database to manage and execute the workflow.

To operate efficiently, or even correctly, workflows often need to satisfy specific properties. Some workflows must run on a regular cadence (daily, hourly, etc.), while others may be event-driven. Many operations require exactly-once execution, but others may be able to tolerate repeated or concurrent runs. Specific services or features also require the ability to rerun parts of a workflow based on external triggers, such as the arrival of new data (data-driven execution).

### 3.6.2. Idempotency, Retries, and Observability

When executing a nontrivial analytics pipeline, the expenditure of resources like memory, CPU, and bandwidth is substantial. These resources incur a cost, whether measured in time or money, and pipelines are often delayed. A successful pipeline not only produces the desired output for the final sensor but also guarantees that in the event of a failure, the output is unaffected or can be recalculated quickly.

An important component of a reliable pipeline is idempotency. According to the Merriam-Webster dictionary, idempotency is a mathematical property of an operator that satisfies the equation $f(f(x)) = f(x)$ for a set S and a defined set of operator f. While the definition is precise, the implication is somewhat abstract: if something can be done

more than once without changing the end result, it can be done more than once. In a pipeline, the ability to repeat part of the pipeline without affecting the outcome is essential. Without that guarantee, it is possible for an executable to write data to a database that is never meant to be reached more than once. The principle underlying idempotency is that any operation that has a side effect can be repeated without modification to the output.

Building within an environment where failures are anticipated lets the designer pursue idempotency. When one part of a pipeline fails and only that one part is retried, it can be retried directly. If that part of the pipeline writes data to a sink, the sink will be updated if it has not yet been reached and silently ignored if it has. Hosts of processors may also have a built-in retry mechanism. If a certain processor fails to respond, it can simply be ignored instead of being hard-killed. Those processors are retained by a queue and retried later until a timed-out limit is reached. Only the last retried copy signals a failure that requires attention, and even that can be included as part of the monitoring process.

## 3.7. Conclusion

By focusing on core data engineering concepts and processes as well as scalable architectural patterns, ideas critical to the design and operation of modern data analytics pipelines are presented.

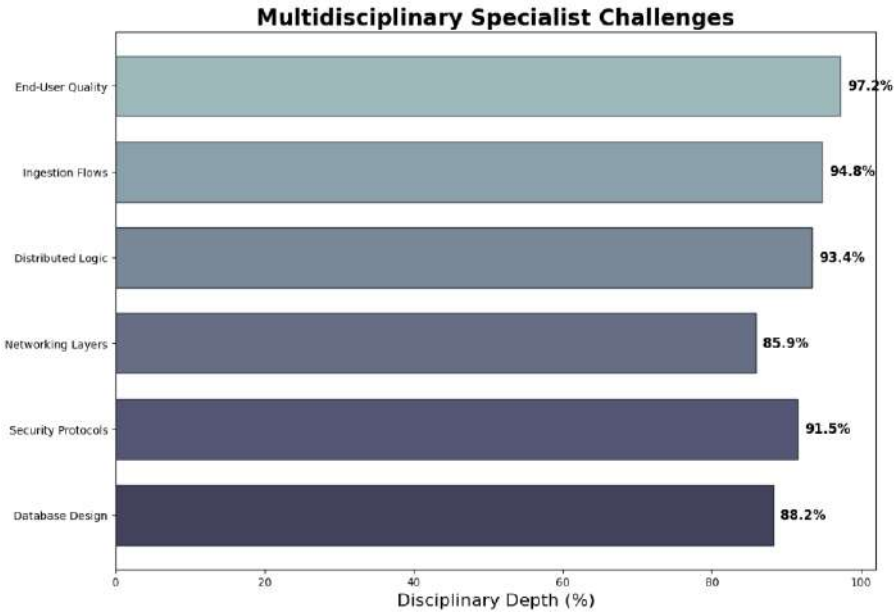


**Fig 3.4:** Multidisciplinary Specialist Challenges

Data engineering is an exciting field poised to underpin further developments in the collection and analysis of data at unprecedented scales. The challenges inherent to these initiatives are the territory of many specialist areas such as distributed systems, databases, networking, and security, among others. Therefore, understanding many concepts across these disciplines is needed to tackle the design and operations of robust data analytics pipelines. The analysis of such pipelines through first principles can clarify the main roles and responsibilities, as well as core workflows and ideas, that constitute the process of data engineering. Designing, developing, and operating scalable batch and streaming architectures, as well as workflow orchestration, are critical to the successful delivery of data analytics solutions and services at scale.

While it is tempting to conform to "big data" buzzwords, attention must not be diverted from the primary goal of these projects: providing quality data to end users. That said, various aspects of data quality can influence designs and operational considerations at every layer of infrastructure. Moreover, as the volume and complexity of data increase, confirming good quality becomes ever more crucial. Lastly, an often-overlooked area of data engineering, workflows that ensure data is correctly ingested, processed, and delivered, play an important role in the successful long-term acceptance of data engineering initiatives.

### 3.7.1. Final Thoughts and Future Directions

A complete understanding of data engineering is critical for the production of robust and manageable data pipelines, which underpin scalable analytics capabilities. Research and innovation in these areas will continue to be critical, as organizations increasingly become committed to data and intelligence as differentiating capabilities.

This work has focused on data engineering fundamentals, without attempting to cover the topic comprehensively. The overview begins by discussing modeling, ingestion, and preparation, followed by architectural patterns for scalability, key processing frameworks, data quality and governance concerns, and the orchestration of pipeline execution. The key themes must all be considered, and new challenges will arise continually, as the volume and diversity of data accelerate and organizational awareness and investment in data as a critical asset intensify.

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