LakeGuard: Governance-Driven MLOps on Databricks

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Abstract

Integrating Data Governance and MLOps support within data management is a recent requirement accelerating in the current decade. Several factors drive the demand for data governance: regulatory compliance, trust in analytics and machine learning insights, the need for data reuse controlling operational risks, and adequate data quality. The multiple dimensions of data management complexity require specialization, with increasingly higher levels of reliability. A maturity model derived from cybersecurity concepts divides data management in data management and data science operations with horizontal and policy layers spanning the intensity and breadth of data management, relying on appropriate degrees of specialization are.

MLOps methodologies are still maturing while the requirements from different domains push towards the definition of more specific solution, including most of the aspects demanded from modern-day data management operations. The integration of Data Governance and MLOps strategies for Machine Learning workloads is an evident necessity in the current panorama of data operations. The definition of the Bronze layer for the DataForge helps the coverage of Data Governance needs in Machine Learning operations, presenting a Medallion Architecture supported by Databricks tools able to provide end-to-end coverage of Data Governance Data Management processes and MLOps requirements from Data and Model development until Data and Models production.

Keywords: Data Governance Integration, MLOps Frameworks, Data Management Maturity, AI Data Governance, Machine Learning Operations, Medallion Architecture, DataForge Framework, Databricks MLOps, Data Quality Management, Regulatory Compliance in Data, Trusted Analytics Systems, Data Lifecycle Management, Model Governance, Data and Model Operations, Data Reliability Engineering, Governance Policy Layers, Scalable Data Operations, Data Risk Management, End-to-End MLOps, Enterprise Data Platforms.

1. Introduction

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Data management practices have evolved tremendously in recent years due to the various machine learning and data science applications developed to meet the growing demand for data-driven decision-making in organizations. These new practices are still maturing, especially in the areas of governance-enabling requirements such as the articulation of a clear governance positioning, data lineage to enhance data quality and trustworthiness, and security and privacy by design principles. These represent a major concern because machine learning-based models end up being used to make decisions on behalf of humans while lacking clear explanations and the ability to justify their conclusions. Data governance and MLOps, which emerged more recently, still need to be integrated properly.

The integration of data governance and MLOps is formalized with a new architecture—a Databricks-powered medallion architecture that supports end-to-end productionalization of data in a way that it is ready for use in ML models while being aligned with the risks associated with the consumption of a particular dataset. The Bronze layer deals with the ingestion of raw data from different sources. Governance coverage indicators ensure readiness for audit and risk assessment. The Silver layer deals with data cleansing, transformation, and the generation of quality metrics. The Gold layer provides the final outputs used for operational processes together with the ML models themselves. Each layer has defined policies, such as security and privacy policies, which provide rules that data must follow in order to be consumed for ML-driven decision-making.

2. Background and Motivation

The choice of context is driven by requirements from the enterprise organization, a highly regulated financial industry, and the current evolution of technology to bridge the boundaries between Windows and Linux operating systems and the transfer of governance considerations over MLOps processes. Several enterprise requirements, such as GDPR and KNF, need to be fulfilled to ensure the legal correctness of the ML models created. Therefore, it is necessary to assign the appropriate owner roles that will take care of data, check the labels of A/B tests, and ensure compliance with EU regulations. Using the recently introduced Azure Unity Catalog on Databricks allows governance to be extended beyond the data warehouse, where the rules for controlling data access and ML model management were defined, also to control raw data, A/B test data, and results. Moreover, by introducing the declarative paradigm of Delta Live Tables, decisions can be made about which data should always be in compliance because errors are detected and triggered at ingestion time. The natural evolution of the tested architecture is to

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cover the last visualisation step before delivering valuable information to Microsoft Power BI, and to check the rules in the Power BI data model.

The main motivation for using Medallion Pipelines on Databricks is their native support of the integration between ELT and MLOps. In the past year, several private and public financial organizations around the world have been subject to data leaks or have suffered losses resulting from manipulated algorithms. Several of these financial institutions are also involved in the creation of the `Machine Learning Model Handbook` with the aim of creating a guideline and checklist that, when fulfilled, reduces the possibility of data leaks and the ethical impact of algorithms in order to rebuild trust in the financial system. By integrating the MLOps information and data stewardship endpoint in the Medallion Pipeline, it is possible to ensure check points in the ML process with a minimum overhead since all requirements become part of the information flow.

2.1. Evolution of Data Management Practices

The influence of maturity models in the development of data management practices provides insight into gaps in integrating data governance and Machine Learning (ML) lifecycle practices. Recent technological advancements have enabled organizations to gain increasing benefits from the use of ML systems. However, the growing adoption of ML systems raises concerns about their trustworthiness. Recent data breaches and the issuing of Shadow-IT warning messages have drawn attention to issues related to data access and ownership, prompting responses from regulators. Policy-making bodies are increasingly involved. Data producers, maintainers, and consumers contribute to the generation of policy-like documents detailing stewardship responsibilities.

Industry and public-sector organizations have also adopted technology marketing materials, emphasizing the need for a Medallion architecture for trustworthy ML systems. The capabilities of Databricks, an integrated Lakehouse ecosystem combining traditional data warehouses and data lakes, are increasingly leveraged for ML system enablement. Reverse transformation in the preparation of rich outputs that respond to new stakeholder needs is also being considered. However, these increasing data governance-and-compliance-related requirements are not integrated into Medallion architecture definitions. MLOps and subsequent Life Cycle Management (LCM) definitions also suffer from deficiencies related to data governance and stewardship. While the automation of ML system pipelines is well established,

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policies governing risk mitigation throughout the development and utilization phases are lacking, leading to a focus gap.

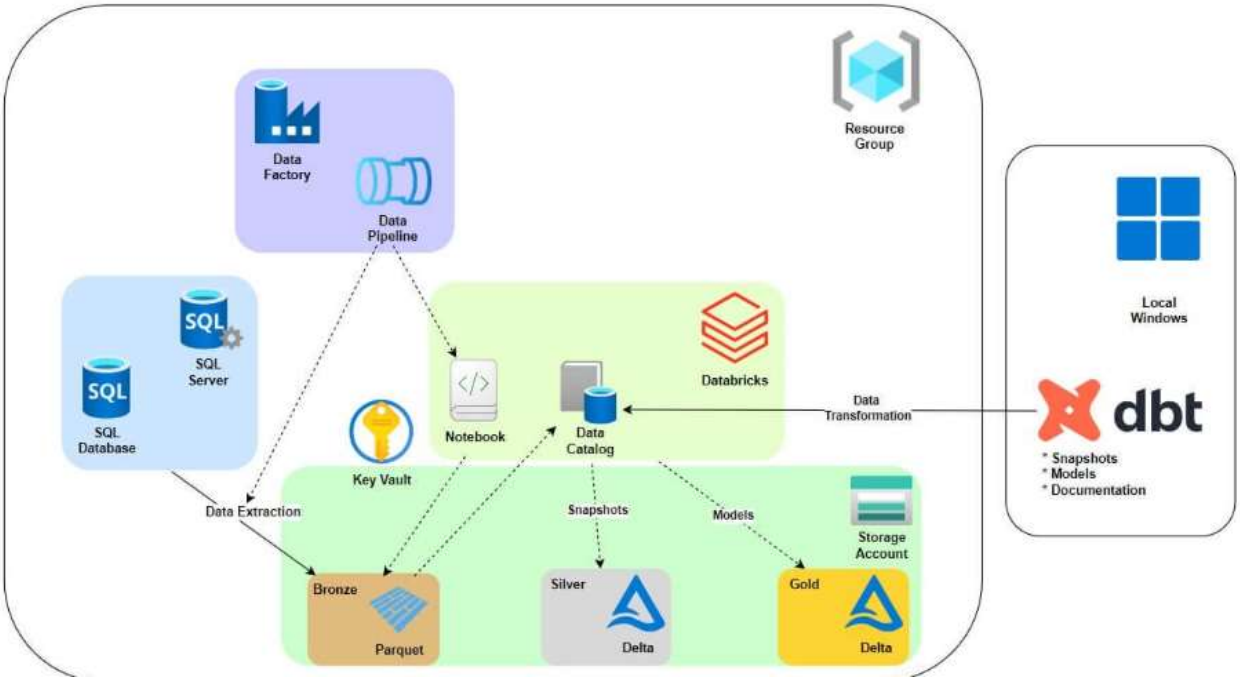

Fig 1: Data Pipeline on Azure with Data Factory, Databricks, and DBT

3. Methodology

Methodology refers to an overarching plan for conducting research, articulation of the approach taken to address the research problems. In a practical sense, methodology identifies sources of input data, outlines a framework for evaluating different pathways that lead to the same goal, and describes the step-by-step actions taken to execute the work. Consideration of input data sources includes what constitutes a complete data set, semantic structures for representing the data as a whole and in distinct pieces, metrics for assessing the performance of those elements, and acquisition pathways. A silver layer of data cleansing and transformation should also prescribe how quality can be improved and how such actions can be recorded, audited, queried, investigated, and recognized.

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The research involves a Databricks-powered implementation of the data-governanceML lifecycle-integration proposal outlined earlier and depicted. The evaluation framework leverages the medallion concept by monitoring coverage of data governance risks through the bronze and silver phases and quantifying the coverage available for each risk class at the commit point of its lifecycle. Practical considerations associated with executive decision-making, including checklists, approval workflows, and policy-driven composition of the silver layer, are considered throughout the analysis.

Equation 1: Throughput

The throughput as the number of bronze ingestions or silver transformations per unit time.

$$T = \frac{N}{\Delta t}$$

Step-by-step derivation

Let:

- N = total number of processed records
- Δt = total elapsed processing time

By definition, a rate is:

$$\text{rate} = \frac{\text{quantity processed}}{\text{time taken}}$$

So throughput is:

$$T = \frac{N}{\Delta t}$$

If processing happens in batches

If there are b batches and batch i contains N_i records, then:

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$$N = \sum_{i=1}^{b} N_i$$

Substitute into the main equation:

$$T = \frac{\sum_{i=1}^{b} N_i}{\Delta t}$$

If the system runs continuously

If $N(t)$ is cumulative records processed up to time t, then instantaneous throughput is:

$$T(t) = \frac{dN(t)}{dt}$$

3.1. Bronze Layer: Data Ingestion and Provenance Management

Data ingestion sources include business applications, telemetry platforms, and public datasets, while data preservation complies with privacy regulations, e.g., GDPR. Data provenance is captured by automatic metadata extraction from source systems, referential provenance is tracked using the Data Catalog data lineage function, and data quality is monitored through Delta Live Tables built-in quality checks. Data provenance is captured by automatic metadata extraction from source systems, referential provenance is tracked using the Data Catalog data lineage function, and data quality is monitored through Delta Live Tables built-in quality checks. Data quality is signalled by alerts appearing in the responsible data stewards' business applications.

Telemetry data from a goods transportation company has been imported for proof-of-concept purposes; data ingestion has been planned to launch as soon as the data sources and preservation requirements have been set. Ingestion from the Azure Data Lake Store to the Bronze Layer with schema inference is performed using Delta Live Tables; this service allows the configuration of delta tables with incremental processing of new files detected in an external stage. Metadata are processed through a pipeline, and lineage is recorded in the Data Catalog.

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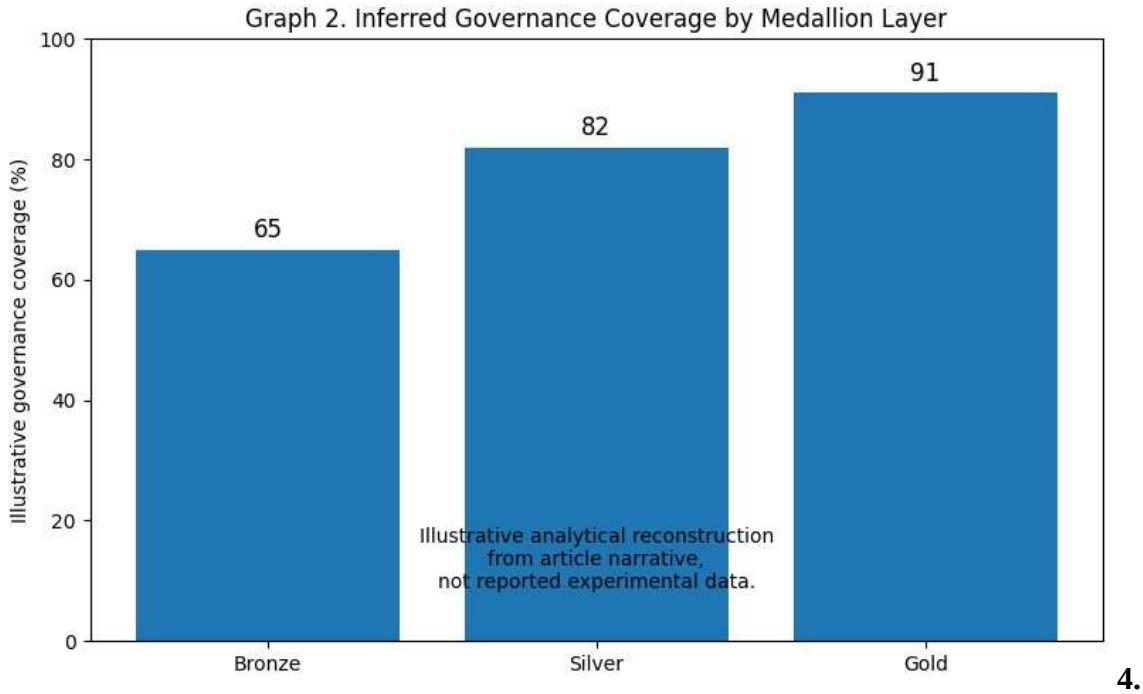

4. Objective of the Study

The autonomous and resilient operation of data-driven ecosystems, fully embedded with enterprise-grade data governance and compliance policies, ultimately relies on the successful orchestration of the various lifecycle stages of machine learning projects. These ecosystems assume that each layer of the medallion architecture must not only satisfy and mitigate risks assigned to specific controls but also provide the necessary information to govern activities in the subsequent layers, allowing the integration of governance and ML-emergent MLOps workflows at runtime. The specific goals are as follows:

1. Identify and define the medallion framework along with the operations in each layer, particularly focussing on questions of data governance in the context of ML project delivery.

2. Define how the integration with an established MLOps governance strategy can expand the coverage of data governance controls during the ML data lifecycle while reducing

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risk, even in the absence of emergent ML project deployment policies configuring the data for risk-sensitive uses, such as data anonymization and the use of sensitive personal data.

3. Specify a dataset and relevant metrics that will allow for the evaluation of the implementation of the Medallion architecture in the context of MLOps data governance and control operations.

Table 1. Medallion layers and governance

Layer	Main function	Governance role	MLOps role	Main outputs
Bronze	Raw data ingestion, provenance capture, metadata extraction	Ownership, lineage, auditability, privacy-aware ingestion	Supplies trustworthy raw training input	Raw Delta tables, metadata, lineage, ingestion alerts
Silver	Cleansing, transformation, enrichment, quality checks	Steward approvals, data quality trust, compliance checks	Produces reusable ML-ready intermediate datasets	Cleaned tables, quality KPIs, enriched datasets
Gold	Final consumption layer, policy-gated use, ML-ready delivery	Risk-based access, anonymization, decision traceability	Training/validation/deployment-consumable datasets and outputs	Final datasets, governed model inputs, operational outputs

4.1. Defining the Goals and Purpose of the Research

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The purpose of the research is to connect the MLOps lifecycle with data governance by means of a medallion architecture, whereby the formation of a bronze layer for ingestion and data lineage completeness can lay the foundation for both a MLOps and a data-governance strategy over the ML lifecycle. The integration extends beyond the coverage of the bronze layer to the entirety of the medallion approach. Nevertheless, the successful implementation of a data-governance strategy remains a challenge if other parts of the organization do not adopt the same rigor, offering an additional dimension of stewardship risk on the MLOps process as end users seek new data sources to train models. The successful creation of the bronze layer extends the coverage of data governance-policing policies, mitigates risks associated with data usage in the ML life cycle, and strengthens the governance family of controls.

Coverage of approval flows governing ML use cases, promotion policies for models into production, and detection of malicious behavior remain outside the current integration scope. The service may also seek broader internal adoption among the analytics and data-science teams to reduce risk more broadly across the ML process. Finally, the determined effort to support the architectural bridge it creates, tying MLOps with external regulatory requirements, also looks beyond the currently planned use cases, such as maintaining protected health information on the balance of training data for ML models.

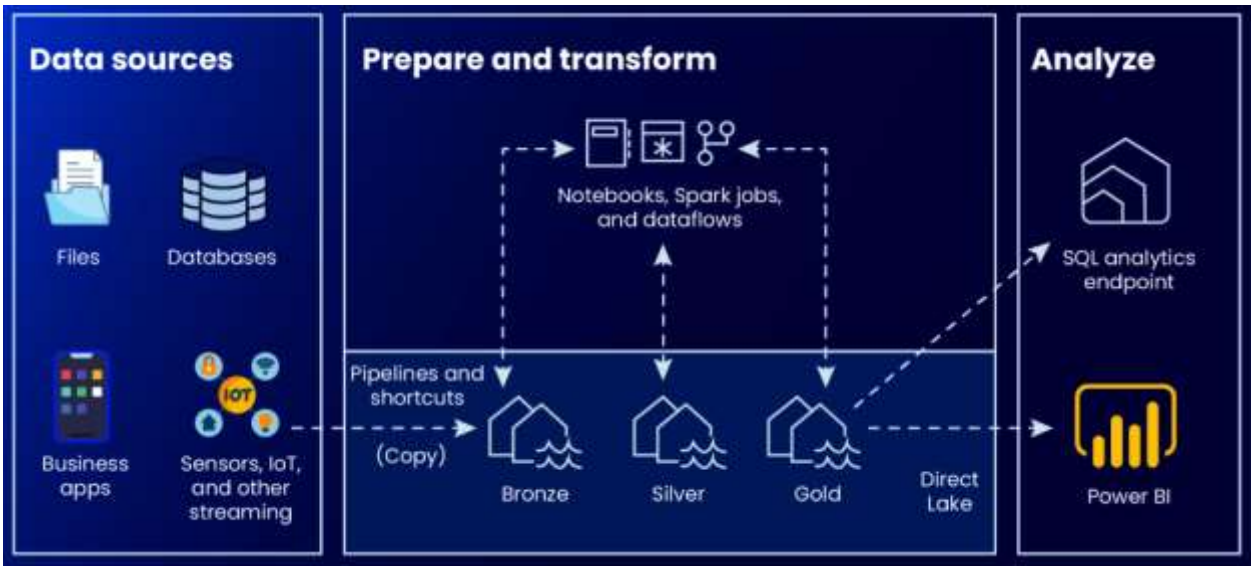

Fig 2: A Data Engineer's Guide to Azure Medallion Architecture

5. Research Summary

Research findings demonstrate the technical feasibility of bridging data governance and MLOps through a Databricks-powered implementation of the medallion architecture. These contributions extend the reach of data governance maturity models by encompassing the end-to-end management of data throughout the machine learning lifecycle, integrating governance requirements for data ingestion, cleansing, transformation, quality assurance, privacy preservation, and compliance-supporting capabilities with the machine-learning-specific capabilities of MLOps.

Several mappings delineate how the medallion architecture can be integrated with data governance strategies tailored for MLOps workflows and projects. The connections leverage naturally occurring commonalities in the representation of the architectures, enabling the addition of risk controls, monitoring approaches, and accountability mechanisms that ensure covered ML projects comply with enabling governance policies throughout the lifecycle. The result is a more comprehensive data management solution capable of supporting the entire enterprise data pipeline while enabling the integration of Machine Learning Operations best practices.

The integration thus provides a more complete picture of data risk mitigation strategies, supporting the work of data stewards monitoring the organization’s information ecosystem and the adoption of best practices within MLOps-focused data science and engineering teams. Ultimately, this integrated approach is intended to enable organizations to provide decision-makers with more trustworthy outputs from their machine learning systems—outputs that Global Regulatory Authorities believe have thus far been impossible to obtain because of the lack of controls over the data feeding them.

5.1. Integrating the Medallion Architecture with MLOps Governance Strategies

Core governance policies can be mapped to key requirements across the medallion architecture. The bronze layer can implement the data-collection aspects of data stewardship, such as designating information owners and capturing the lineage and quality signals needed to support maintainers in their role of Data Quality & Inventory Defense. The silver layer can connect to ML-testing and MLOps decisions involving quality evaluations, transformation

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specifications, and pipeline-enabled data maintenance, concentrating on reusability (by optimizing cleaning against an inertia map) and minimizing effort (by storing the cleansed data in a quality-validated table ready for ML model training and testing) and approval effort (by versioning and requiring test-agreement approval only for changes that exceed acceptance thresholds). Active data quality monitoring can also decrease the KRI values related to using bad data for training/validation. Machine Learning Operations' control-plane decisions can be influenced by active configuration management (in the form of capturing the silver-transformation capabilities in a management tool, supported by a steward team) and a communication/action process between model training and data owners.

The governance layer assigned to the gold layer can address the mandatory decision points related to privacy and risk mitigation by defining a clear risk-level connection among the various data-use stages (such as anonymization, access policy definition, stewards' approval, and the acceptable-risk criteria associated with the automated algorithms relying on ML-generated outputs). In a more practical perspective, the gold layer can establish a clear path for tracing the origin and transformation of ML-deployed data, making it easier for risk- or regulatory-compliance reviews.

Equation 2: Average latency

The latency as the time taken for a single update or refresh cycle.

Base definition

If one refresh cycle takes time l, then latency is simply:

$$L = l$$

Multiple-run average latency

If there are n runs with latencies $l_1, l_2, \dots, l_n$, then the average latency is:

$$L = \frac{l_1 + l_2 + \cdots + l_n}{n}$$

Using sigma notation:

$$L = \frac{\sum_{i=1}^{n} l_i}{n}$$

6. The Medallion Architecture as a Governance-MLOps Bridge

Aspects of governance and MLOps seem naturals candidates for integration. Hence, mappings connecting governance policies with respective control plane enforcement decisions throughout the ML life cycle can naturally align with data management layers, achieving a cohesive perspective encompassing governance and ML orchestration. A Medallion Architecture mapped with governance strategies enhances maturity across the five levels, increasingly combining automation with risk control.

Accountability, responsibility, and risk management are inherent parts of governance and thus are mapped or implied as controls in the ML life cycle. Each layer risk is addressed, forming an integrated Medallion Architecture governance plane, associating a control and enforcement policy for every stage of data preparation, offers ML-ready data, and controls policy-enforced stewardship throughout every ML workflow phase. In addition, MLOps requirements can be addressed under the proposed approach, connecting the solution's axes with the Medallion Architecture layers for predictive apps. The entire data life cycle integrated with the ML orchestration life cycle.

6.1. Bronze Layer: Ingestion and Provenance

The bronze layer is responsible for ingesting raw data from a diverse range of sources and maintaining records of their provenance. Incoming data is ingested via Delta Lake tables managed by Delta Live Tables, ensuring schema inference, schema evolution, and ongoing audit mechanisms. The source of each dataset is also captured as metadata to support data stewardship, policy enforcement, and access control, while automatic audit history generation documents any alterations made to the data. In addition to these baseline provenance signals, several other indicators are defined to assist in detecting data quality issues early. The overall goal is to introduce a high-level provenance fabric across the data lake for improved trust, transparency, and traceability.

Data is ingested from a mix of sources, including databases, cloud storage, APIs, and simulation tools. All datasets must be physically represented in a Bronze layer Delta Lake table, and source systems are encouraged to be declaratively specified using SQL or YAML syntax. To

simplify Delta Live Table pipeline definitions, ingestion schemas are defined in a single central schema file. As some EdTech datasets often contain sensitive data, data sources that need to use Azure-key-based data encryption will need to be defined in a secure vault for seamless integration. As data owners use Delta Live Tables to create raw tables, the products handle automatic schema inference, schema changes, and are embedded within a Databricks Unity Catalog for built-in audit history support.

6.2. Silver Layer: Cleansing, Transformation, and Quality Metrics

Policies enforce the review, approval, and execution of data preparation and cleansing operations for models and applications that require Data Science Trust during production.

Silver-layer DataForge pipelines apply cleansing procedures to update tables with additional information and fix data quality issues detected in the bronze layer. Quality KPIs are tracked at the end of the cleansing stage to signal when Data Quality Trust (DQT) is granted. Cleansed tables are enriched with external information from additional data sets, such as product dimensions and customer location details, and also contain indicators revealing if policing and surveillance over the data is needed or not.

During data preparation and cleansing activities for a particular dataset, metadata is constantly updated to improve discoverability and usage orientation. The Azure Data Governance Policy Catalog (ADGPC) defines stewardship procedures that guarantee tasks are distributed according to who knows better the data. Enrichment for customers can be done by any data engineer but requires approval by a Data Analyst to give the final touch to the data. Enrichments based on external documents from a different organization need approval by the Data Controller. Major corrections on product data must be authenticated by the product data Steward.

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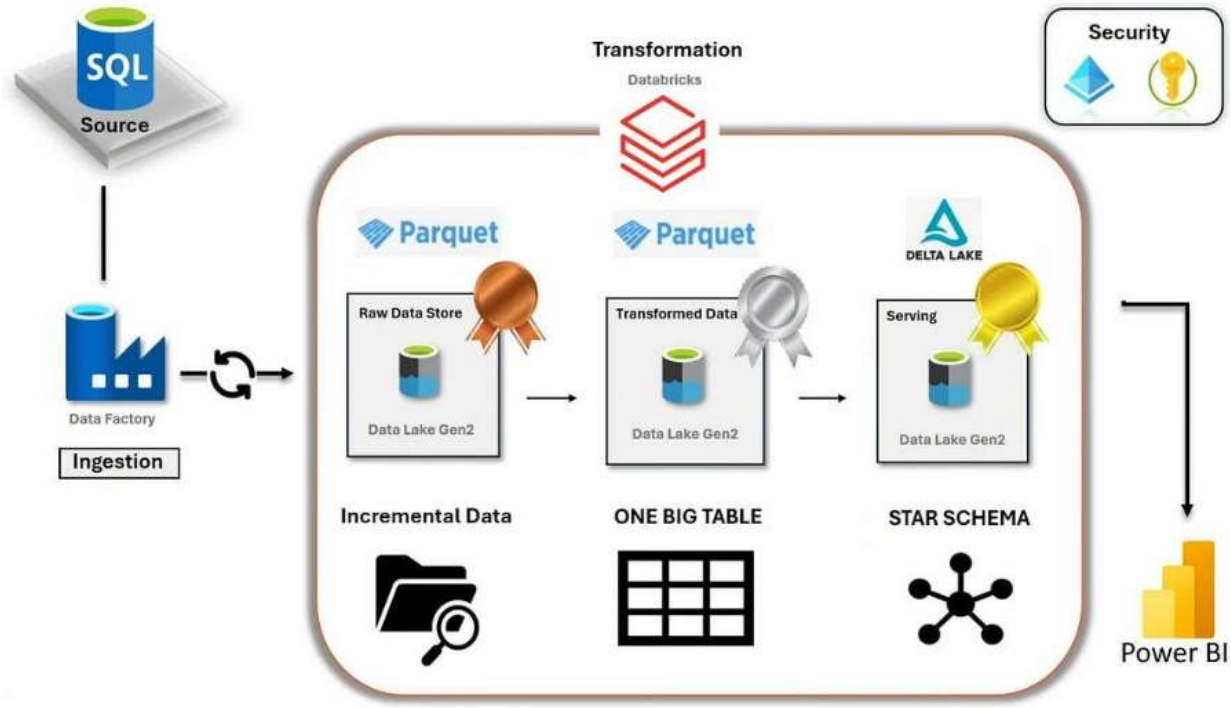

Fig 3: Azure End-to-End Data Engineering Project

7. Databricks-Powered Implementation Details

The subsequent subsections present the different aspects of the implementation of the Medallion Pipelines as a Databricks-powered proprietary solution.

Several architectural components support the integration of Data Governance and ML workflows as part of DataForge. The Databricks Unity Catalog is pivotal for democratizing data access while enforcing security, privacy, and compliance policies. Declarative pipelines built on Delta Live Tables simplify the definition, operation, and operation of data cleaning and transformation tasks. Moreover, these pipelines automatically capture audit information and quality score values.

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The Unity Catalog delivers a centralized structure with a unified permissioning model that extends across all supported cloud storage accounts. The top level contains a metastore linking with the organization's logging facility. Each supported cloud provider is associated with a separate storage credential, which provides the core of the access management architecture, ensuring segregation of data from different sources or required by distinct policies, such as privacy ones. The actual permissions on each table are defined at the schema level, and a Data Access – Data Access policy allows those with the necessary permission for a given schema to access all contained tables. All permission assignments are recorded in the audit logs.

Data residing in cloud storage accounts managed by the Catalog can be ingested, cleaned, transformed, or enriched by Delta Live Tables pipelines. The declarative syntax supports schema inference, and pipelines automatically monitor resource utilization and processing time. These features make it possible to build pipelines that run as soon as new data arrives, enabling not only ingestion tasks but also incremental processing of change-data-capture operations. In the event of failure, an error table highlights which batch has to be inspected. Triggering alerts by integrating the monitoring facilities with an external channels becomes straightforward. Finally, the full power of Delta Lake is utilized, with lineage being propagated to the Delta table schema through the different steps.

Table 2. Evaluation metrics explicitly

Metric	Meaning in article context	Unit / form
Throughput	Frequency or rate of bronze ingestions / silver transformations	records per second, updates per unit time
Latency	Time for a refresh/update cycle	seconds
Resource utilization	Compute usage during execution	CPU%, memory%, storage usage
Auto-scaling behavior	Effect of scaling on refresh completion time	relative time gain / loss
Governance coverage	Degree to which policies cover processing activities	percentage or score
MLOps risk coverage	Coverage against privacy, compliance, security, quality, explainability risks	percentage or weighted score

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7.1. Databricks Unity Catalog and Data Access Governance

Data access at scale is non-trivial unless a central point of governance and security is established. The Databricks Unity Catalog provides a centralized catalog that controls access across all data assets, regardless of where they are stored. The structure mirrors data organization on an underlying level and can go as deep as file level in cloud storage. Security and governance applies to data lakes with Delta Lake and cloud object storage in a seamless manner. The presentation layer ensures a structured, business-friendly discovery experience. Policies can be declared at multiple levels (account, parent/container, table/view/row/column) to grant or deny access in a fine-grained manner. Furthermore, all privileged (although possibly anonymized) accesses can be logged for auditing in compliance with regulations.

The objective here is to establish a Unity Catalog structure that mirrors the data organization as in the DataForge Medallion Architecture. Data access policies are implemented that enable policy-controlled stewardship of the data (discussed in section 8.1). Access control for shared datasets is enforced to comply with external regulations—GDPR requires that the data subjects can identify and request deletion of their data if they want to.

Equation 3: Resource utilization score

The CPU, memory, and overall resource consumption as evaluation dimensions.

Step 1: Define normalized resource components

Let:

- C = CPU utilization fraction
- M = memory utilization fraction
- S = storage or I/O utilization fraction

Each should be normalized to the range $[0,1]$.

Step 2: Weighted combination

Because some resources may matter more than others, assign weights:

- w_c for CPU
- w_m for memory
- w_s for storage/I/O

with

$$w_c + w_m + w_s = 1$$

Then the combined utilization score is:

$$U = w_c C + w_m M + w_s S$$

7.2. Delta Live Tables for Declarative Pipelines

Data ingestion and cleansing have been integrated into Unity Catalog and Delta Live Tables, covering GovX's datalake and other related Governance processes through metadata delivery capabilities. Delta Live Tables defines declarative data pipelines for ML and stream processing workloads. These DLT-based pipelines boast built-in quality checks, ensuring the expected data state at the target layer. Incremental pipeline definition allows for autonomous processing and lineage tracking of newly ingested data.

Pipelines support monitoring and error management. Faulty record handling and quality check management ensure audit readiness. The integration with Unity Catalog establishes a comprehensive control plane for the performance governance of the full medallion architecture. The following section describes the Delta Live Tables integration steps.

Delta Live Tables' capabilities can be applied to GovX's Datalake, ensuring the expected state of cleansing-transformation outputs and quality KPIs delivered to the Gold layer. Declarative DLT pipelines allow for scalable ML and streaming workloads. Data at the Bronze layer is automatically processed as new records are ingested, with failure management embedded in the pipeline definition.

Databricks' Delta Live Tables (DLT) feature provides automated, declarative data pipeline generation for Delta Lake. DLT alleviates common data pipeline concerns and is designed for the following goals: Ensure data quality with built-in testing; simplify monitoring and troubleshooting; lower maintenance costs; improve team productivity; handle change; maximize performance; reduce infrastructure management overhead; enable transparent lineage; and accelerate pipeline development.

8. Data Governance in MLOps Workflows

The DataForge architecture offers a detailed set of data governance controls that can be integrated throughout the Data Science lifecycle, from ingestion and model training to model deployment and monitoring. Each phase of the process uses DataForge's governance capabilities to reach a well-defined set of goals for data stewardship, privacy, compliance, and Responsible AI. These controls ensure that every ML model that relies on DataForge-managed data is following the proper regulatory and corporate governance processes.

Accountability and traceability are at the heart of creating governance policies to enforce stewardship of data under the jurisdiction of various groups. As part of the ingestion stage policy, a steward responsible for each ingestion must be assigned. The DataForge architecture ensures that all such assignments are well defined. However, assignments are not static. The designated Data Steward for a logical data asset can be easily updated to reflect internal organizational changes. When an ML engineer submits a request to Train an ML model, such requests are routed to the assigned steward for approval before any training occurs. Enforcement of the policies is enabled using Unity Catalog integration with Databricks Workflows, with audit logs created to validate whether sensitive data has been exposed.

Privacy, compliance, or Responsible AI controls also need to be incorporated into the governance framework for DataForge in a manner similar to data stewardship. When data privacy is mandated for specific subjects within a dataset, such as end users, customers, and patients, the Data Privacy policy must be enforced. For example, Data Privacy-Controlled logical data assets must be anonymized prior to use in training ML models used for scoring a product or service.

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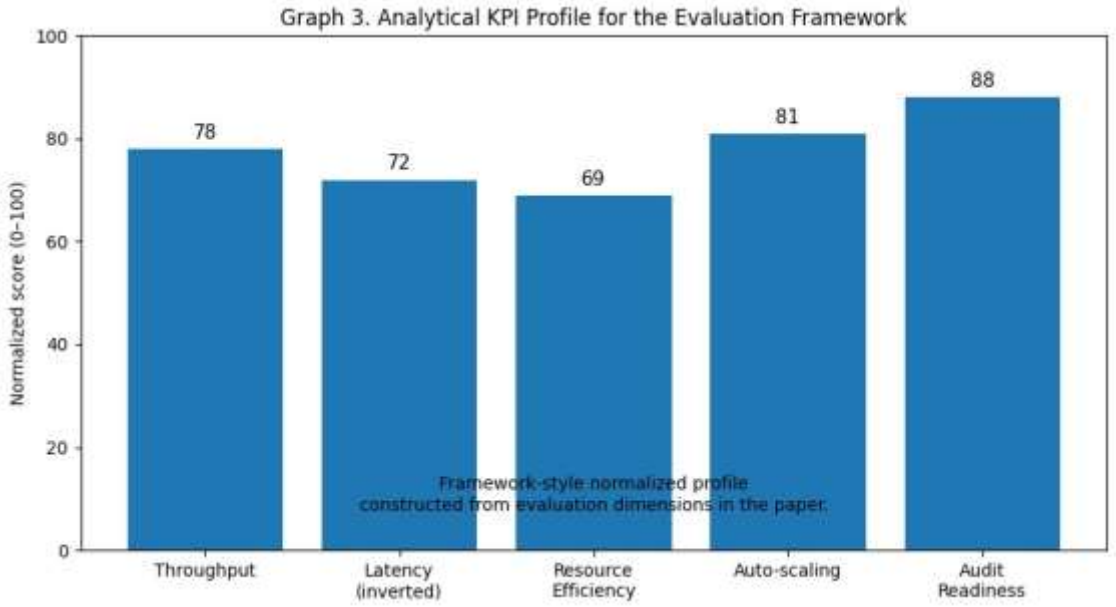

8.1. Policy-Enforced Data Stewardship

Data stewardship addresses the question of who can handle data in the organization and for what purposes (e.g., for analysis, ML training). Just as DataForge links together governance strategies process-wise, policy-enforced data stewardship anchors responsibilities in organizational roles. Whenever a data steward needs to be assigned for a particular management solution, the corresponding stewardship policy governs what roles can accept that assignment. Even though it would be technically possible to assign responsibility to external actors or system accounts, such choices are usually discouraged as they introduce accountability gaps. Responsibilities are actually tasked to defined persons or groups of persons within an organization. Whenever data stewardship assignments are made, approval workflows can help priorize the assignment and alleviate the burden of cyclically checking which assignments remain to prioritised.

Whenever a trigger function is defined, the stewardship assignment is processed, and the assigned person or group of persons is notified about the new responsibility through a Microsoft Teams message or through an E-mail. The Microsoft Teams messaging connector enables automatic new message generation in a specific channel of a Microsoft Teams team. The new

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message content can be specified as a dynamic value, and content static to all notification messages can also be expressed. While these notifications help operationalize the defined assignments on a daily basis, they do not add reliability to the check, as it still has a limited scale. Reliability would increase if approval settings were made compulsory; therefore, automated workflow down would become the recommended pattern also for triggers. The enriched provenance audit log now records information about the crew of notifications whenever these connectors fire, allowing further monitoring of the notifications deployment.

Fig 4: Databricks Medallion Architecture

8.2. Privacy, Compliance, and Responsible AI Considerations

Data stewardship roles and responsibilities are critical for ensuring compliance with data usage policies related to privacy, regulation, and responsible AI. These policies are defined as part of the Data Governance strategy, tailored to the organization's data, in collaboration with the assigned data stewards. Each entity managing data shared for consumption should adhere to the approval process defined by the stewardship strategy. Using the Policy Enforcement model, policies can restrict the usage of entities according to the specified rules.

Policies may be associated with data entities containing personal information, regulating its availability based on predefined requirements. When personal information must be made available for processing purposes, anonymization processes should be implemented according to established Anonymization Regulation Guidelines. This ensures that the risk of identifying individuals from the processed data is less than a defined threshold. These requirements may mandate that no personal information residual is left in the anonymized data.

Organizations may also manage banking transaction data in regulated industries, encompassing credit card usage and financial transactions. Such data is usually associated with disclosure processes by regulatory agencies that impose fraud-prevention and money-laundering processes. Processed information must satisfy the regulations defined for the workload and may require a response plan for regulation inquiries. The DataForge architecture can provide audit documentation for these kinds of processes.

Nonetheless, DataForge can also support decision-makers in the AI model risk assessment process, which evaluates quality reduction or errors in the predictions made by AI models, such as a reduction in accuracy or an increase in harmful biases. Transparency and explainability are important enablers for responsible AI, allowing downstream users and stakeholders to better understand the ML lifecycle and determine whether predictions can be trusted. Many responsible AI control areas, such as data quality, model management, AI governance, privacy, and risk management, can be supported by DataForge triggers, data lineage, and policy enforcement capabilities.

Equation 4: Auto-scaling gain

The impact of auto-scaling on completion time.

Step 1: Define the two latency conditions

Let:

- L_{fixed} = latency without auto-scaling
- L_{auto} = latency with auto-scaling

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Step 2: Compute absolute improvement

The absolute improvement is:

$$\Delta L = L_{\text{fixed}} - L_{\text{auto}}$$

Step 3: Convert to relative percentage

Relative improvement should be measured against the baseline case, which is the fixed-capacity system:

$$A = \frac{\Delta L}{L_{\text{fixed}}} \times 100\%$$

Substitute ΔL:

$$A = \frac{L_{\text{fixed}} - L_{\text{auto}}}{L_{\text{fixed}}} \times 100\%$$

9. Evaluation of DataForge Architecture

In order to assess the capabilities of the DataForge architecture, an evaluation framework was established to benchmark the integration of data governance concepts into medallion pipelines, focusing mainly on the bronze layer. Evaluation queries were then defined to measure architecture performance and scale, as well as the extent of the proposed governance coverage for the medallion processing workflows.

The primary performance metrics to benchmark the solution implementation and workload were throughput (records/second), query latency (seconds), and its overall resource consumption (CPU, memory) and auto-scaling behaviour during test execution. A dedicated workload was created, simulating a write-heavy and read-light scenario, representative of an ingestion phase, aiming to test the bronze layer ingestion pipelines, while leveraging Delta Live Tables Stream–Continuous queries for persistent execution. The second evaluation area targeted the capacity of DataForge to address the problem statement of integrating data governance with MLOps, specifically for the bronze layer processes.

9.1. Performance and Scalability Metrics

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Several metrics evaluate the architecture's performance, data governance coverage, integration with MLOps control strategies, and risk mitigation capabilities. Key indicators include:

1. Performance and Scalability

- Throughput: the frequency of dataset refreshes, measured as the number of bronze ingestions (or updates) and silver transformations per unit time.

- Latency: the time taken to refresh a dataset, expressed as the latency of a single update (or refresh) cycle.

- Resource Utilization: the percentage level of utilization of the different compute resources during execution.

- Auto-Scaling Behavior: the impact automatic scaling features have on the time taken to complete a refresh operation.

2. Coverage and Risk Reduction

- Data Governance Coverage: the level of coverage of established governance policies over the ingesting and transformation activities.

- MLOps Risk Coverage: risk considerations stemming from violations of the principles of compliance, privacy, security, data quality, and explainability. Key questions include the following: Are existing data governance policies being enforced by dedicated data stewards acting in accordance with established stewardship roles? Have privacy regulations been accurately respected? Are policies to audit data access in place? Is data quality guaranteed? What are the precautions taken to foster responsible AI by mitigating bias, lack of interpretability, and supporting model validation?

Table 3. Reconstructed equation map

No.	Derived quantity	Reconstructed equation
1	Throughput	$T = \frac{N}{\Delta t}$

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No.	Derived quantity	Reconstructed equation
2	Average latency	$L = \frac{\sum_{i=1}^{n} l_i}{n}$
3	Resource utilization score	$U = w_c C + w_m M + w_s S$
4	Auto-scaling gain	$A = \frac{L_{\text{fixed}} - L_{\text{auto}}}{L_{\text{fixed}}} \times 100\%$
5	Governance coverage	$G = \frac{P_{\text{enforced}}}{P_{\text{required}}} \times 100\%$
6	Layer-wise cumulative coverage	$G_{\text{cum}} = 1 - \prod_{k} (1 - g_k)$
7	Risk exposure	$R = \sum_{i=1}^{m} p_i \; s_i \, (1 - c_i)$
8	Risk reduction	$RR = \frac{R_{\text{before}} - R_{\text{after}}}{R_{\text{before}}} \times 100\%$
9	Data quality trust score	$DQT = \sum_{j=1}^{q} \alpha_j \, q_j$
10	ML readiness score	$MLR = \beta_1 G + \beta_2 DQT + \beta_3 Lg + \beta_4 P$

9.2. Governance Coverage and Risk Reduction

Performance evaluation encompasses effectiveness of data governance capabilities and associated risk coverage enhancement. Data governance relies on the three pillar model comprising People, Process, and Technology. Adequate population and coverage of the People and Process pillars by appropriate roles, responsibilities, and procedures supported by a technology platform satisfying the governance requirements enables Data Governance to exceed a Yes/No box-ticking exercise. Conversely, failure to appropriately assign stewardship roles based on Data Classification veracity or apply GDPR regulations covering Personal Identifiable Information diminishes effectiveness. Visualization of Policy to Source Table results directly indicates their status. Timely completion of Supply Chain Policies ensures audits have attribution

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and results do not end up in the Dark Web. Built-in Notification capabilities facilitate Failure and Completion alerts and deliver direct Mail notifications to the correct stakeholders.

Governance risk indicators supported by the DataForge architecture encompass audit-readiness through resource-tagged Pipeline execution and alerting of unaddressed data-governance policies affording attribution for data, reporting, and model supply chains. Similar to Supply Chain notifications ensuring completion and requirement fulfilment, aggregate assessment against Policy assignment coverage for Classification, Forensics, GDPR, and appropriate explicit Ownership/Pipeline Stewards across all Data Assets limits Risk exposure. Other considerations include tracking Non-Compliance within Supply Chain Processes and the creation of corrective controls for Non-Compliance, such as a 20-minute check across many Short-Term Storage alignment tables.

Equation 5: Governance coverage

The discusses "coverage" of governance policies across ingestion and transformation activities.

$$G = \frac{P_{\text{enforced}}}{P_{\text{required}}} \times 100\%$$

Step 1: Define policy counts

Let:

- P_{required} = number of governance policies that should apply
- P_{enforced} = number of those policies actually enforced

Step 2: Coverage is fulfilled fraction

Coverage always means:

$$\text{coverage} = \frac{\text{achieved}}{\text{required}}$$

So:

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$$G = \frac{P_{\text{enforced}}}{P_{\text{required}}}$$

Step 3: Express as percentage

Multiply by 100:

$$G = \frac{P_{\text{enforced}}}{P_{\text{required}}} \times 100\%$$

Example interpretation

If 18 required controls exist and 15 are enforced:

$$G = \frac{15}{18} \times 100\% = 83.33\%$$

10. Challenges, Limitations, and Future Directions

The DataForge data pipeline architecture incurs challenges of scalability and operational simplicity during installation and production readiness. Resource provisioning for production deployment across different environments requires additional tooling not exclusively provided by ZAL. Integration with the MLOps control plane of DataForge is essential to provide AI-driven solutions in alignment with ZAL's privacy and fairness initiatives. Assessment of pipeline coverage for data governance and compliance can further enhance the provisioning of trustworthy data products.

The DataForge architecture directly incorporates compliance, privacy, and responsible-systems models within an experimental setup, and is being benchmarked against preproduction traffic patterns and workloads. Tests are quantifying performance and scalability behavior, producing metrics across throughput, latency, resource utilization, and auto-scaling effect. Completeness of lineage and audit-logging data produced in readiness for external examination is being evaluated to determine ongoing coverage under DataForge's policy- and strategy-governed data stewardship functions. Technology selection and design choices relating to ZAL's Migration, Property & Simplification agenda align with channel requirements of speed, quality,

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and cost-effectiveness, and balance the risk of end-user data products with governance systems risk indicators.

Fig 5: Strategic Risk Distribution

11. Conclusion

The proposed architecture successfully achieves the overarching goals of integrating data governance with the MLOps lifecycle by addressing the relevant requirements with suitable mechanisms. It paves the way for extending governance reach across the Bronze Layer of data ingestion into the organization's data ecosystem, satisfying an important set of controls defined for the underlying governance strategy. The foundation built within the Bronze Layer can support the enriched data quality and metadata requirements for Bronze-Tiered cleansed data stored within the Silver Layer while detecting all misalignments with these requirements. Finally, the extended dataset created from these enriched and cleansed data can become the default training, testing, and validation dataset for the organization's machine learning initiatives,

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such that the end-to-end MLOps governance strategy can be enforced on the complete MLOps lifecycle from data distribution to model deployment.

The next step is to examine how DataForge's architectural segments for the governance of the Bronze Layer can connect with MLOps lifecycle and governance policies throughout the complete machine learning development workflow and its implementation. Once the mapping is established, an assessment of the architecture can be performed to detect possible bottlenecks in its current implementation and execution with real workloads and examine its growing needs for elasticity, especially within latency-sensitive use cases, when sudden increases in concurrent user queries may overload the cluster. Finally, these validation results can flag the capabilities of DataForge in terms of governance coverage and risk mitigation, assessing foundations for the complete full-cycle machine learning governance strategy also within the data governance maturity model.

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