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Automating Data Governance and PII Compliance Using Unity Catalog in AI-Driven Data Ecosystems

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Abstract

Tailored data ecosystems enable organizations to continuously generate and derive business value by processing data into valuable information using AI workflows and pipelines. The wider adoption of AI, however, introduces new risks, such as model bias and unethical decision-making. Recent developments demonstrate the importance of establishing an AI governance framework to minimize risks and set up accessible, secure, and responsible AI systems. Based on numerous high-profile cases that reveal AI models leaking personally identifiable information (PII) – which, when exposed, poses significant legal compliance risks and reputational damage – a risk-based, regulator-driven approach to PII governance and protection in AI pipelines is also gaining traction. Recent advances in Zero Trust Architecture and principles of least privilege, along with the concurrent evolution of PII-related regulations, provide further impetus by advocating for data minimization.

Against this backdrop, automation of data governance and PII compliance across all AI workflows as part of a tailored data ecosystem becomes a pressing need. Automation improves accessibility and efficiency; enables organizations to have their own cloud-based data ecosystems, yet "outsource" their regulatory compliance implementation; and, with adequate governance, supports responsible AI development. A formal analysis defines the goals of establishing automated governance in a Unity Catalog environment typically employed by organizations to create tailored data ecosystems.

Keywords : Data Governance; Data Stewardship; Personal Identifiable Information; Privacy Regulation; Data Classification; Data Protection; Continuous Improvement; Risk-based Approach; Data Minimization; Accessibility vs. Privacy.

1. Introduction

Data Governance underpins any AI-powered data ecosystem and establishes a trusted foundation for PII compliance. Personal Data and Sensitive Data Classification must therefore be automated across the Data Asset Life Cycle to ensure an appropriate standard of data protection and confirm that Data Protection Principles such as Data Minimisation are complied with. However, achieving such automation remains a significant challenge. The PII Protection Framework formalises the design of data ecosystems that automatically detect the presence of PII, restrict access to the minimum necessary level, and implement privacy-enhancing processes such as Data Masking, Anonymisation, Pseudonymisation, Alternative Data Use and Model Auditing. Automation functions for each of these activities can be specified, and the approach is supported with empirical testing. Automation of Security Policy Control, Data Masking, Detection of PII leakage risk in AI Models using the AI Governance Classification Scheme, detection of potential Data Breaches and the Control of Assertion are demonstrated in a retail case study. The Application of the framework in Databricks Unity Catalog, and the Automation of Classifiers, Policies and Access-Monitoring are illustrated in a Telco-case study. Other automation functions are design but not yet implemented.

The establishment and operation of Data Governance relies on the definition of key Performance Indicators and the Support of a Maturity Model covering the key non-key activity areas of Procedure, Process, Tools, Technology, Training and Culture. The Maturity Model enables assessment against a pre-defined set of criteria and the identification of areas requiring improvement or enhancement. Continuous improvement is achieved by capturing Data-driven Feedback and revisiting each stage of the Automation of Classification, Access Control and PII Protection functionality. Governance feed-forward loops enable the automatic retraining of Classifiers, refinement of Classification Rules and Automation of Policy Specification for RBAC, ABAC and Dynamic Masking Controls.

1.1. Research design

Personal data has turned into a recurring monetary asset for many facets of daily life. An increasing amount of activities create or exchange information regarding people, leading to operations leveraging data related to individuals. The emergence of AI-based services makes the generation, exchange, and exploitation of personal data even more lively. Data sources have changed into production environments with models being trained using external data provided through training and use services. The access of data by the user through different channels motivates the creation of a cross-channel market that uses the knowledge of each channel, increasing the sexual power of the whole. Artificial Intelligence is at the base of this revolution, applying techniques to easily and automatically gather, connect, anonymize and exploit information from these sources and improve these processes.

To dominate this market, companies must guarantee the profitability of the processes without being blamed for the excessive exploration of personal data. Different regulations have appeared in different countries with rules to guarantee user privacy, but controlling the privacy of a user should go beyond being simply legal compliant. Governance should go further with the intent of being socially acceptable and guaranteeing citizens know how their personal data is manipulated. It is important to minimize the use of personal identifiers by public agencies and private companies to mitigate risks during manipulation. Guarantees should be provided for all the phases of the AI model life cycle from design to deployment.

Fig 1: Data Governance and PII Compliance Using Unity Catalog

1.2. Scope and Objective

Achievement of the stated objectives requires the automation of advanced classification, policy-driven access control, row-level security, privacy-preserving data minimization, PII detection and risk mitigation, and responsible data retention, all integrated within a governance framework. The automation considers enterprise data ecosystems supporting analytics, data science, and AI workloads. Detection and reaction mechanisms automates PII-related issues in analytics workflows, while generative AI operations receive additional safeguards against exposure.

Equation 1: Precision

Step-by-step derivation

Let:

- **TP** = true positives = items correctly predicted as sensitive
- **FP** = false positives = items incorrectly predicted as sensitive

Then the set of all positive predictions is:

$$\text{Predicted Positive} = TP + FP$$

Precision is the fraction of correct positive predictions among all positive predictions:

$$\text{Precision} = \frac{\text{Correct Positive Predictions}}{\text{All Positive Predictions}}$$

Substitute the counts:

$$\boxed{\text{Precision} = \frac{TP}{TP + FP}}$$

Interpretation in this article

If the Unity Catalog classifier labels 100 columns as PII and 80 truly are PII, then:

$$\text{Precision} = \frac{80}{100} = 0.8$$

That means **80% of flagged assets were correctly flagged**.

2. Foundations of Data Governance and PII Compliance

Data governance and compliance constitute fundamentals of responsible data management and usage. Automated solutions operating within Unity Catalog can facilitate fulfilling the principles of data governance, manage categories of data minimization and protection, and address privacy legislation. These guarantees can be summarized as the automation of data governance and personal identifiable information (PII) compliance, with the objective of continuous policy improvement.

Data governance is the set of responsibilities and practices exercised by data stewards, data owners, and data consumers to manage the availability, usability, integrity, and security of the data used in an organization. The principles of data governance identified by the Data Management Association International serve as a foundation for automation. Addressing these principles in the context of AI-driven data ecosystems involves establishing an environment for continuous assessment and improvement of the underlying data governance controls. A risk-based approach remains key in designing data protection and privacy solutions. The Privacy by Design and by Default principles articulated in the General Data Protection Regulation stipulate that privacy considerations must be factored into the decision-making when developing new products and services, ruling out by default the usage of PII whenever possible. Appropriately defining the data domains involved in enterprise workloads contributes to achieving these authentic objectives. Moreover, a metrics-based approach and the adoption of a suitable maturity model provide the feedback necessary for controlling, assessing, and improving the specified services over time. Finally, dedicated controls can address the risk of PII exposure by AI models during both the training and inference phases of model development and execution.

2.1. Data Governance Principles

A strong governance model should ensure that data management objectives align with the organization's business goals and that data governance decisions are taken by the appropriate people. First, these stakeholders should be responsible for deciding what data is important for the organization and how it should be managed. Data governance models usually map data stewardship and data ownership roles. Data stewards oversee the management of a specific data domain and ensure that data is accurate, available, and secure. They define common business terms, measure data quality, and communicate issues to data users. Data owners are usually departmental leaders who understand their domain data best.

Data governance policies should provide the guidelines and approval mechanism that delineate who has the authority to determine how risks concerning the respective data domain should be managed. The lifestyle and management of data must follow documented procedures that consider legal compliance and reflect the organization's risk appetite. Accountability

must be established for people involved in the development, operation, and use of AI systems, including data governance automation.

2.2. Personal Identifiable Information and Privacy Regulations Data governance schemes often identify sensitive data, such as personally identifiable information (PII) or payment card information (PCI), that are under different privacy regulations. These regulations represent varying degrees of strictness depending on the jurisdiction and its potential impact on the users themselves. Such regulations are usually a mix of permission and prohibition, inhibiting some risks while encouraging others through restricted conditions. When a company offers services in multiple jurisdictions around the globe, exposure of an identified data element to any of the above regulations is essential during the classification and governance processes. Organizations may want to eliminate or reduce PII exposure in AI models, while others may be forced to comply with GDPR, PCI-DSS, HIPAA∗, or similar legislation, warranting the identification and sanitization of any PII information contained therein. Therefore, PII and privacy regulation handling assumes great relevance in the automation process.

PII may be defined as any combination of information that can be used to distinguish an individual or, when combined with other personal or identifying information, can be linked to a specific individual whose identity is applicable in a given context. Countries have adopted their own privacy regulations over time, with varying levels of severity. A simple map highlights four major regulatory groups, according to their risk levels: strong (GDPR–Europe; LGPD–Brazil; PDPA–Singapore), medium (PCI-DSS–global), soft (HIPAA–USA; CCPA–California), and nascent (CCPA–California). The business impact of violating these regulations increases with time. Institutions tend to adopt a risk-based approach model by treating sensitive data carefully while being flexible with others. Nonetheless, an increasing number of breach incidents are leading organizations to take privacy issues more seriously and comply with these regulations, especially when separate regulatory actions affect the company's bottom line. The business regulators have become so strict that data exposure may lead to a lawsuit in extreme cases. PII exposure risk mitigation is thus vital when complying with strong regulations.

Fig 2: Personal Identifying Information (PII)

3. Methodology

The proposed automation is realized as a technical and methodological approach for building the above-mentioned end-to-end automated data governance foundation applicable within the Databricks Unified analytics platform with Unity Catalog. The key components and architecture of this solution are visualized in the figure below. The metastore that maintains the

system catalog of data assets and associated governance metadata is complemented by a data governance catalog; this catalog, besides holding governance metadata itself, enables the definition of granular governance processes that deliver classifier rulesets, set up lineage logging, impose workload execution constraints, generate data access policies, specify PII risk-detection procedures, and feed continuous testing processes. Multiple interfaces support integration with external systems, for example, automated model performance testing or periodic governance audits.

The automated data classification and sensitive-data-identification capabilities bolster the documentation and governance foundation of the platform by generating and maintaining a clearly defined, populated business-friendly data taxonomy. Formalized data labeling and lineage information complement the classification layer, thereby reinforcing its importance in the global automation design. The automatic detection of PII data records and information flows underpieces additional sensitive-data-specific governance processes such as policy-driven access management and row-level security.

Equation 2: Recall

Step-by-step derivation

Let:

- **TP** = true positives
- **FN** = false negatives = sensitive items missed by the classifier

Then the total number of actual positives is:

$$\text{Actual Positive} = TP + FN$$

Recall is the fraction of actual positives that were captured:

$$\text{Recall} = \frac{\text{Correct Positive Predictions}}{\text{All Actual Positives}}$$

Substitute:

$$\boxed{\text{Recall} = \frac{TP}{TP + FN}}$$

Interpretation in this article

If there are actually 200 sensitive columns and the system detects 180 of them:

$$\text{Recall} = \frac{180}{200} = 0.9$$

So the governance automation catches **90% of the sensitive fields**.

3.1. Architecture and Core Components Automation of data governance and PII compliance in AI ecosystem relies on a four-role architecture where key capabilities include a unified, multi-cloud catalog (Unity Catalog), a centralized metastore, policy enforcement, and automated classification. Core components are explicitly designed to operate either within Unity Catalog framework or to interface with it: classification rules and workflows scan tabular datasets for data sensitivity, classification, and lineage information; roles automate storage policies, perform dynamic data masking and implement row-level security; classifiers and workflows for data exposure detection enhance safeguards for data-limited training; and the model risk management framework assists with integrated evaluation of governance controls.

All elements are available as open-source code within GitHub project, can be repurposed for private-cloud deployment outside Unity Catalog without loss of automation, and achieve end-to-end integration of monitoring and control for data protection against test or attacked leaks of sensitive data by exposed artificial intelligence models. The automated controls are explicitly mapped to main privacy-preserving objectives of minimization, anonymization and pseudonymization, and

demonstrate tangible benefits for the Open Data community. Design-centric documentation facilitates comprehension, deployment, and extension.

3.2. Data Classification and Metadata Management Well-defined taxonomy and labeling schemes for data and AI models, complemented by comprehensive lineage records describing data propagation and transformation, are fundamental to effective governance. Established metadata management standards further enhance quality and reusability. Automated classifiers, with governance rules based on their decisions and the related tags, enable the integration of classification into operational data flows. Key classification aspects are therefore addressed and a holistic automation framework for data governance using Unity Catalog is proposed.

A wide range of methods exists for the discovery of sensitive information, classification of content, and tagging of data. Major approaches include manually defined rules, lexical matching techniques, supervised machine learning, unsupervised machine learning, and deep learning. Rule-based classifiers are straightforward and transparent, though their coverage depends on human effort and knowledge. Machine learning classifiers are typically more scalable and have wider coverage, although they introduce additional challenges related to training data availability, quality, representativeness, bias, and interpretability. Recurrent evaluation and retraining are also fundamental to maintain classifier quality. Labeling data in advance to identify category membership can facilitate supervised development or domain-specific tuning of state-of-the-art implementations. The performance of these classifiers can be measured in terms of traditional classification metrics (precision, recall, and F1 score) or information retrieval metrics (map and ndcg score).

Fig 3: Data Classification and Metadata Management

4. Objective of the Study

The objective is to automate data classification, thus identifying sensitive data that require specific levels of protection in the governance workflows, making the knowledge graph reflect any detection of personal identifiable information to ensure they are not present in AI training and inference processes.

Automated classification concerns the application of classifiers that share the same rule-based approach or that are driven by machine learning techniques. The performance of the classifiers can be evaluated using precision and recall metrics and compared through the F1-score value. The tests are considered validated when they close the loop with a human-in-the-loop process that allows an operator to assess the true positive and false positive predictions returned by the classifier. Subsequently, the validated classifier can be applied to the catalog.

The second aspect encompasses the development of data access and protection rules. Policy collections are extended to the catalog, and these policies are then aligned with the classified information. The Union Catalog supports role-based access control (RBAC) and attribute-based access control (ABAC) at the same time; thus, the automated access management mechanism works according to the combination of both rules. The access dynamic masking features of the Delta Lake format also guarantee that access to sensitive information is masked according to the requirements of the organization. Finally, the flow of data in the catalog is monitored, allowing the catalog to maintain the knowledge of the information it manages. If a row-level security mechanism is also in place, the masked and perturbed data will respect it.

4.1. Automated Classification and Sensitive Data Identification

Effective and efficient data governance requires timely and accurate information about the data landscape, classification, and identification of sensitive data. Stable rule-based classifiers are suitable for domains with well-defined de-identification rules or closed-category domains. However, ML-based classifiers are preferable in open-category domains, as they classify data into categories that will be absent in the training data. A machine learning model for PII detection is implemented as it can learn to categorize any in-domain data rather than just detect the presence of a small set of PII types.

The classification performance of both classifiers is evaluated, and publicly available samples from the appropriate domain are used as validation data. Metrics are computed using the de-identification metadata and public datasets originating from Krishnan et al. and Savedra et al. Samples annotated with PII data that support Hurst & Möller's classification categories are used to evaluate GDPR compliance. Addressing GDPR compliance creates a clear rationale for the organization. The context around motivation and use-case impacts the final decision and technical suitability of a PII-capturing classifier within a sensitive AI-based ecosystem.

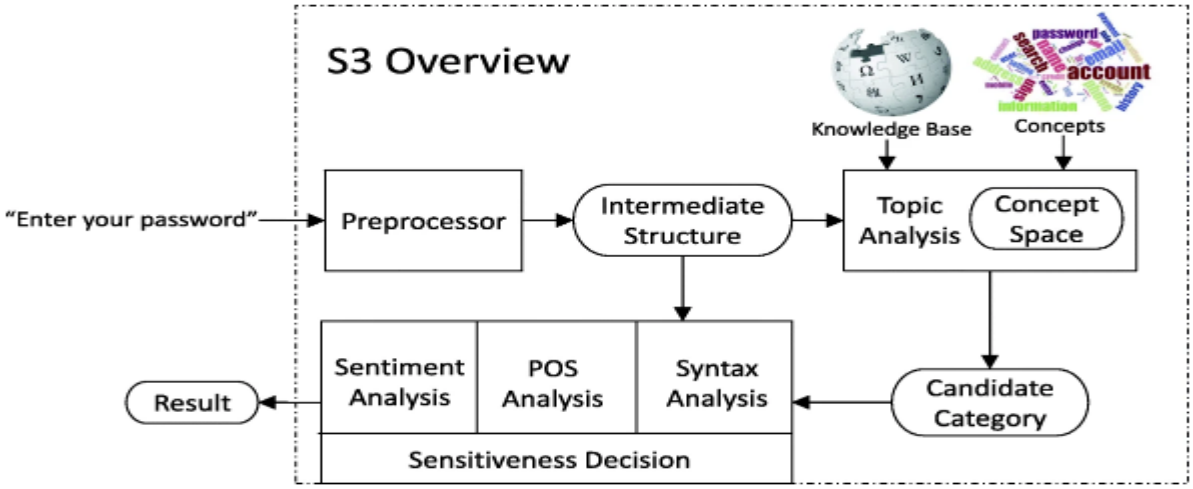


Fig 4: Automated identification of sensitive data

4.2. Policy-Driven Access Management and Row-Level Security

Access management within the Unity Catalog relies on a security model that combines role-based and attribute-based access control. Whenever possible, access to sensitive data should be moderated by a unified control policy that can limit it to essential personnel only. Dynamic data masking adds another layer of protection, ensuring that secret or classified information is never revealed to user roles that could abuse it. Row-level restrictions allow PII elimination or even potential anonymization during data extraction by excluding unwanted segments from the dataset. All policies governing these measures can be automatically generated, routinely evaluated, and administratively monitored.

As data classification automatically labels the data assets, a business decision framework that determines which sample and population attributes must be used to implement RBAC, ABAC, marking, and row-level policies can be encoded as a set of rules or controls. Uniform application of policies through evidence-based rules enhances reliability and credibility while allowing the data protection governance strategy to be aligned with GDPR principles. Use of business guards systematically at the extraction phase enables Data Protection by Design, reinforcing the affirmation that privacy should be built in.

Equation 3: F1-score

Step-by-step derivation

The F1-score is defined as the **harmonic mean** of precision $P$and recall R:

$$F1 = \frac{2PR}{P + R}$$

Now substitute:

$$P = \frac{TP}{TP + FP}, R = \frac{TP}{TP + FN}$$

So:

$$F1 = \frac{2 \cdot \frac{TP}{TP + FP} \cdot \frac{TP}{TP + FN}}{\frac{TP}{TP + FP} + \frac{TP}{TP + FN}}$$

Now simplify numerator first:

$$2 \cdot \frac{TP}{TP + FP} \cdot \frac{TP}{TP + FN} = \frac{2TP^2}{(TP + FP)(TP + FN)}$$

Now simplify denominator:

$$\frac{TP}{TP + FP} + \frac{TP}{TP + FN} = \frac{TP(TP + FN) + TP(TP + FP)}{(TP + FP)(TP + FN)}$$
$$= \frac{TP[(TP + FN) + (TP + FP)]}{(TP + FP)(TP + FN)}$$
$$= \frac{TP(2TP + FP + FN)}{(TP + FP)(TP + FN)}$$

Now divide numerator by denominator:

$$F1 = \frac{\frac{2TP^2}{(TP + FP)(TP + FN)}}{\frac{TP(2TP + FP + FN)}{(TP + FP)(TP + FN)}}$$

The common denominator cancels:

$$F1 = \frac{2TP^2}{TP(2TP + FP + FN)}$$

Cancel one TP:

$$\boxed{F1 = \frac{2TP}{2TP + FP + FN}}$$

5. Research Summary

Research findings clarify data governance and PII handling considerations associated with AI-based data ecosystems. Two prioritized areas for automation emerge: reducing sensitive data exposure and controlling PII in training and inference workflows. Risk-level mitigation is further exemplified by a Unity Catalog-based implementation, reaching a data governance maturity tier. Although ideally suited for generating datasets without PII, the method is adaptable to data-minimization contexts, effective at masking or scrubbing data destined for public exposure, and can prevent exposing PII in underlying AI models.

End-to-end privacy preservation in AI pipelines is addressed by Data Science and AI workflows consuming/accessing sensitive data sources such that the resulting PII exposure can be monitored/measured and privacy breaches avoided. All flows are provided with mechanisms to detect PII leakage, warn upon exposure at training time, and block access during

inference when real entities are being processed. Together with the supporting feedback loop integrating the PII Classifier, these capabilities strengthen automated protection without needing extensive manual annotation.

5.1. Data Minimization, Anonymization, and Pseudonymization Techniques Data minimization is a scatter approach in which only the information necessary to complete the task at hand is collected and stored. Anonymization involves eliminating or altering personal identified data from a database, making it impossible to identify individuals. For example an individual could be removed from a photo used as marketing material. If the condition can no longer be determined, such as a facial recognition part detection box for an individual being removed, then the individual could be considered as anonymized. Pseudonymization is an additional technique whereby a natural person cannot be identified without the use of additional information which is kept separately. For example, names in a database could be replace with a random number, but a second data file is kept that links individuals with their number.

Although anonymization and pseudonymization can be seen as desirable techniques it has been said that making datasets anonymized or pseudonymized can be hard and often marked that although used, they should be carefully evaluated under the risk-based definition for the country or region if they are still classified as PII as much more data than other countries might be relate data exposed. Hence care needs to be taken to ensure true anonymization for the country or region it is being used in.

Equation 4: Risk score for sensitive-data exposure

Step-by-step construction

A standard governance risk score can be built from:

- **Sensitivity score** S
- **Regulatory severity** R
- **Exposure likelihood** L
- **Business impact** B

We define a weighted aggregate:

$$\text{RiskScore} = w_1 S + w_2 R + w_3 L + w_4 B$$

where:

$$w_1 + w_2 + w_3 + w_4 = 1, w_i \geq 0$$

So the complete equation is:

$$\boxed{\text{RiskScore} = w_1 S + w_2 R + w_3 L + w_4 B}$$

Why this follows from the paper

The paper discusses:

- strong vs medium vs soft regulations,
- risk-based handling of sensitive data,
- policy generation based on risk,
- and mitigation priority.

That naturally implies a weighted score.

Example

Suppose:

- $S = 0.9$
- $R = 1.0$
- $L = 0.7$
- $B = 0.8$

and weights:

- $w_1 = 0.35$
- $w_2 = 0.25$
- $w_3 = 0.20$
- $w_4 = 0.20$

Then:

$$\text{RiskScore} = 0.35(0.9) + 0.25(1.0) + 0.20(0.7) + 0.20(0.8)$$
$$= 0.315 + 0.25 + 0.14 + 0.16$$
$$\boxed{\text{RiskScore} = 0.865}$$

5.2. Detecting and Mitigating PII Exposure in AI Models AI models can inadvertently expose PII during training or inference. Training-time exposure occurs in supervised learning when the model learns statistical correlations between PII and other attributes; exposed PII might be implicitly contained in the model. Inference-time exposure may also arise during model usage if the model generates new tokens that can be reverse-engineered as sensitive or develops other forms of leakage as identified through testing. The risk of sensitive data being reconstructed from generated images adds to privacy concerns.

Mitigation strategies exist for both exposure types. First, training-time exposure may be reduced through measures like data minimization and anonymization, or by using generative adversarial networks (GANs) to add noise without sacrificing performance. Tagging training samples can support auditing by identifying training sources. Second, inference-time exposure can be curtailed by filtering output tokens, employing differential privacy on training data or model weights, post-training hardening, and developing a testing strategy to evaluate levels of generated information leakage from both generative AI and transformer models.

6. Result

Outcomes from the empirical evaluations and case illustrations are presented next, starting with an automated classification and access-control use case.

Case Study I: Automated Classification and Access Control

The effectiveness of the proposed classification and access-control automation was validated using an operational data ecosystem. Administrators configured 19 classification rules to detect sensitive data, including address, biometrics, financial account and payment card, health, identity, national identification number, and sexual orientation. Cloud service-sensitive labels were also assigned. The labels were automatically applied to 13,000 data objects in AWS S3 buckets, Delta tables in Databricks, and Microsoft Azure SQL databases. Instance-level and column-masking access policies were generated for four sensitive cloud services based on a risk-based approach. Control events indicated that 132 users from 25 business units accessed sensitive data across six cloud services within eight days. Sixty-three percent of the user interactions with sensitive data matched the expected pattern, with sensitive data being used to enhance product offerings and customer experience while complying with privacy regulations. The results demonstrated the feasibility of automating sensitive-data detection, policy creation for role-based and attribute-based access control, and integration with data usage activity monitoring. A risk-based approach with risk-scoring tables also improved the success rate of policy detection.

Case Study II: End-to-End PII Protection in AI Pipelines

An end-to-end data-engineering and data-science workflow was created in the Databricks cloud environment to showcase PII training and leaky model protections. The workflow consisted of three components and three cloud services. The

training-time protection labeled two Delta tables in the data lake, indicating the presence of PII data in columns, while the masking protection generated an instance-level masking policy for a Microsoft Azure SQL database table. The leak-detection component included an architecture diagram and configuration setting for integrating the AI model code with the privacy-leak-detection classifier. These end-to-end-use-case capabilities facilitated the assessment of PII data residing in the training data and the implementation of mechanisms to identify privacy leakage in AI services. The data-engineering and data-science teams received an automated alert indicating the presence of sensitive data for masking through the end-to-end governance workbench. The data-engineering team also updated the training data to mitigate the privacy-leak exposure risk.

Equation 5: Access-control decision equation (RBAC + ABAC)

Let:

- U= user
- D= data asset
- A= access request
- $RBAC(U,D) \in \{0,1\}$= 1 if role-based rule allows access
- $ABAC(U,D) \in \{0,1\}$= 1 if attribute-based rule allows access

The combined access decision can be modeled as logical AND:

$$\text{Permit}(U,D) = RBAC(U,D) \wedge ABAC(U,D)$$

If we encode Boolean values as 0/1, logical AND becomes multiplication:

$$\boxed{\text{Permit}(U,D) = RBAC(U,D) \cdot ABAC(U,D)}$$

Step-by-step reasoning

1. Access is granted only if the user's role is authorized.
2. Access is also granted only if contextual attributes match policy.
3. Therefore both conditions must be true simultaneously.

So:

- If $RBAC = 1$, $ABAC = 1$, then Permit $= 1$
- Otherwise Permit $= 0$

Example truth table

$RBAC$	$ABAC$	$Permit$
1	1	1
1	0	0
0	1	0
0	0	0

6.1. Case Study I: Automated Classification and Access Control A proof-of-concept deployment illustrated the automation of sensitive data classification and access governance in a unified data platform for machine learning, analytics, and business intelligence. Key components included data classifiers for public and sensitive label assignment, a PII policy governing access control, and audit logging of policy-triggered events. The classifiers achieved high recall and F1 scores. The access-control policy successfully restricted access to labelled data, with violated access requests being consistently denied.

The automated architecture integrated rule-based and machine-learning classifiers into the data platform. Descriptions of the classified data-types, recurrence characteristics of policy-triggered events, and access requests from users without

policy authorisation verified the end-to-end functioning. The deployment demonstrated the potential benefits of automated data governance in the context of personal identifiable information, supporting the overall research agenda and acting as a blueprint for future implementation at scale.

6.2. Case Study II: End-to-End PII Protection in AI Pipelines End-to-end PII protection across all phases of AI pipelines is illustrated with a data-mining workflow leveraging travel reminders. Sensitive data is automatically masked in training and evaluation datasets, supporting privacy-preserving studies. Different users observe distinct data during testing, yet all gain insight into potential PII leakage from the model. The combined effort achieves essential objectives of compliance management: minimizing PII exposure in the ecosystem while employing the captured data to enhance the deployed AI application.

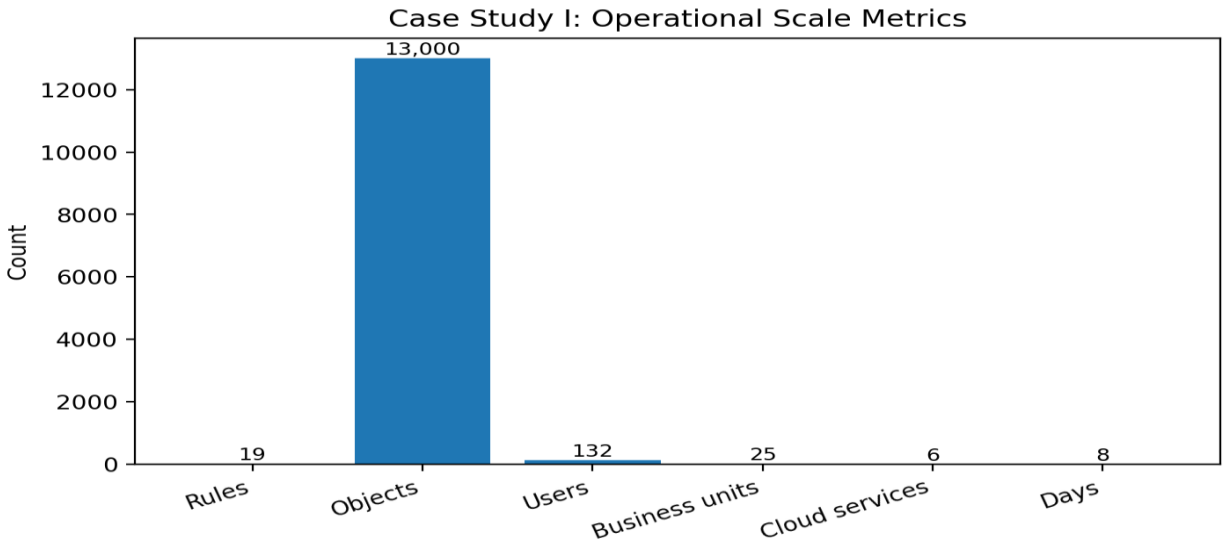
While case study I tested only automated classification and access-city-pair policies, this more complex example spans complete PII protection over a hypothetical travel-data mining-and-retrieval scenario. Regulatory goals encompass data minimization, preserving privacy in model training and testing, and auditing model leakage risk. The underlying travel-reminder dataset informs users of upcoming journeys based on retrieved flight details. Imagine a PII-aware set of users building and assessing the model to evaluate its risk.

7. Governance Metrics, Maturity, and Continuous Improvement

Key performance indicators and maturity models provide a structured framework for assessing the effectiveness of automated data governance. KPIs yield numerical evidence for of the current adequacy of governance measures and guide their continuous improvement, while maturity tier descriptions support self-assessments of the organization's level of capability. Regular measurement of these metrics facilitates activation of data-driven feedback loops that inform retraining of the employed classifiers and machine learning models, fine-tuning of the governance automation policies, execution of model liability audits, and periodic audits of the overall governance framework.

The proposed automated governance capabilities for AI pipelines, developed and displayed as within the Unity Catalog ecosystem are rigorous and drive PII compliance requirements within organizations using AI processes. As with any such framework, they require KPIs to ensure appropriate usage. A set of KPIs are proposed that map onto the automated capabilities, with an accompanying set of maturity tiers. Data-minimization techniques have also been addressed, with an emphasis on both monitoring for PII detection and mitigation during the training and inference stages of models. Possible trade-offs of accessibility against protection in the context of automation of the PII-categorized-based controls are also noted.

Make data-driven decisions through governance automation, controls, and process enhancements, where necessary, based on data profiling, deter potential violations with the necessary AI and non-AI controls, checks, balances, and enhancements, support data dominiality aspirations via regulator-mapped change controls to a central authority, ensure that personal data is not exposed for any use cases via the combination of control measures, leakage detection, and AI process-monitoring controls, and enable the AI-readiness of mitigation techniques for PII detection and mitigation in all use cases.



7.1. Key Performance Indicators and Maturity Models The following define the governance automation key performance indicators (KPIs), maturity model, measurement intervals, and continuous-improvement mechanisms.

The Tone Analyzer service offers real-time emotional-intensity feedback to dynamically augment user experiences. Automated assessment rates create an objective measure for the PII protection present in machine-learning models at both training and inference times; three performance categories allocate mitigation status through a traffic-light system. Category-1 leakage detected in supervised classification triggers a mask applied to the input data. Category-2 leakage detected in unsupervised or semi-supervised classification requires extra care in handling the models; explicit consent from users is mandatory during usage. Models falling into category 3 are not affected during inference but must be audited for PII exposure regularly. Training-time and inference-time safeguards can be easily implemented in any AI pipeline.

Data Governance Maturity Model. Continuous improvement requires ongoing reassessment to ensure that proper security controls are in place and functioning as intended. An invested third party should execute audits at regular time intervals aligned with supporting stakeholders. Model accuracy and policy coverage should also be reviewed. Information gathered can feed either the automated model retraining or the policy-refining frameworks. Data minification and PII-detection automations reduce risk but may introduce bias in AI models. Recalibrating the PII classifiers by adding a PII class to the AI model can remedy this issue. Users' accessibility and rights can further influence the degree of automatic data protection applied; business tolerance and data sensitivity should dictate the risk-benefit trade-off. A four-tier governance model can support usability, user and data protection, and maturity of automated solutions.

7.2. continuous improvement through Feedback Loops and Automation Data-mining applications primarily benefit from data-driven feedback techniques, which involve leveraging insights derived from model performance assessments to refine the underlying classification or risk estimation models. These techniques can also be integrated into governance automation efforts, with the objective of improving respective automatic governance components at defined intervals. Such components can, in turn, influence the evolution of other automation components.

To illustrate, the implementations of automated classifiers for protecting sensitive attributes in data currently defined under PII regulations are performance-tested at regular intervals to ascertain whether any gradual degradation has occurred. When this degradation exceeds an acceptable threshold defined in the governance policy, the model retraining process is initiated, generating a more up-to-date automatic governance component to take the place of the existing classifying function in the pipeline's metadata management domain. A similar approach applies to the automatic policy generation component, where it is determined whether any privacy-related policies require refreshing. Static rules defined during setup offer indications regarding the frequency of periodic data-mining model retraining or privacy-related policy updates—or even whether such updates are required at all. Ultimately, however, periodic readjustments must be made, based on policy definitions and technology evolution, to the other automatic governance components that support the PII protection requirement for the end-to-end AI pipelines.

8. Challenges, Risks, and Ethical Considerations

Automating data governance and PII compliance in AI-driven data ecosystems through Unity Catalog

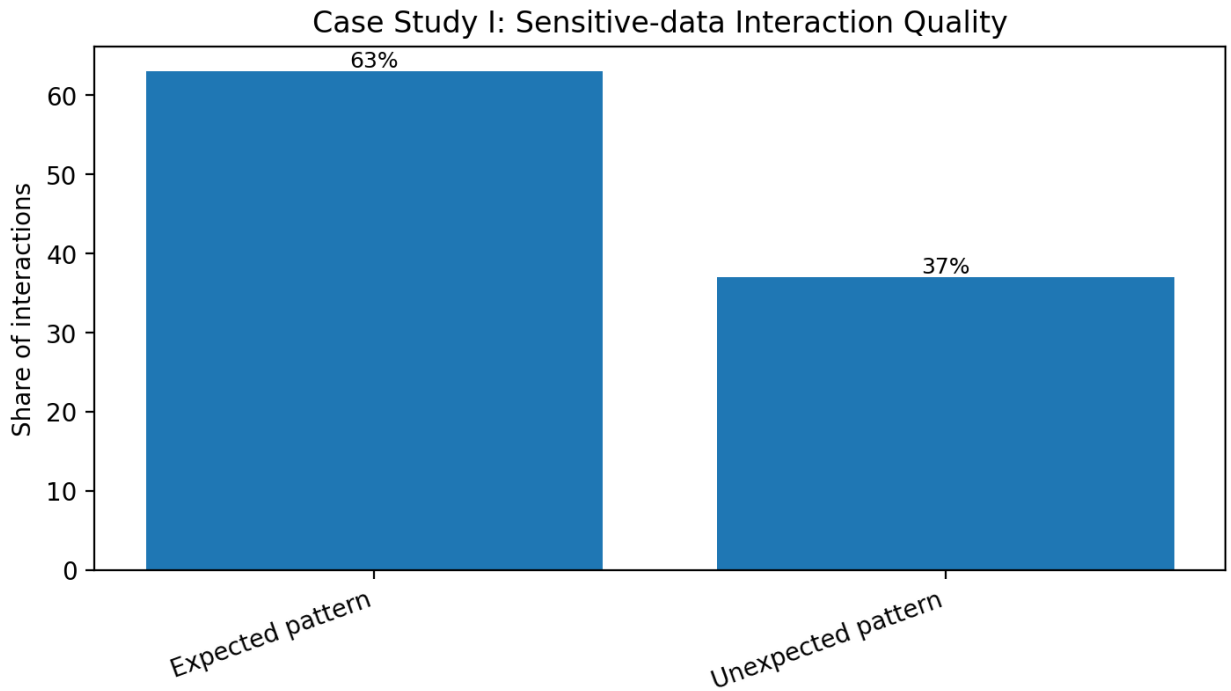
Trade-offs emerge in the design and utilization of technology-enabled governance mechanisms. In particular, the accessibility of data for legitimate use and the need for deploying compensating tools and techniques come into tension with the need for ensuring privacy protection. A poorly designed governance structure may increase the sharing and use of personal data by limiting the efficacy of privacy-enhancing technologies—such as anonymization or pseudonymization—and rendering them ineffective against disclosure risks. However, this paradox can be resolved through appropriate prioritization and recurrent reviews to incorporate lessons learned from incidents: exposing sensitive datasets externally can trigger sufficient investigation of the underlying data governance practices and data systems in use to warrant a stronger emphasis on regulatory compliance during the next cycle.

Automated governance functions face additional challenges related to the risks of biases, lack of transparency, and absence of explanation. These drawbacks are not unique to governance: every stage of the machine learning (ML) process may introduce biases alongside the algorithms deployed, and such biases may subsequently propagate into the final model. Biased models can replicate existing discrimination or introduce new forms of unfairness in the predictions. The inherent black box nature of ML models makes it difficult to understand the causes behind the predictions, which has emerged as

an important concern, notably in high-stake applications where decisions impact people's life. Even in non-high-stake domains, a recognized lack of transparency may inhibit adoption by end users. Consequently, bias, transparency, and explainability constitute crucial aspects of responsible AI that require incorporation throughout the process, from the inception of the ML project to the deployment phase.

8.1. Trade-offs Between Accessibility and Privacy The operations of contemporary organizations often necessitate collecting, processing, and storing large amounts of Open Data, that is, large amounts of data related to people or events. Tragically, some organizations share these Open Data more than necessary. The privacy risks of exposing sensitive data are well understood, leading many organizations, especially Internet Service Providers (ISPs), to be obligated to protect personal identifiable information (PII) or data that can be used for identification purposes of an individual. Artificial Intelligence (AI) solutions typically consume Open Data with the objective of learning a predictive/declarative model that can predict the future or declare a certain fact from the past. Concerns about leakage of PII from AI model have led to the impression that operations of some organizations have become too restrictive. For instance, many recommender systems nowadays do not have a certain offer because users of certain characteristics are not found on the customer base. At the same time, the industry is very concerned about the usability of AI solutions and the perceived complexity by the users/tomianto of such intelligent systems. Although there's still a long way to go, during the last decades much effort has been put by researchers in the subject of PII privacy in AI systems.

Framing the earlier observations, the goal of the construction is to demonstrate the automation of data governance and PII compliance in AI-driven data ecosystems through Unity Catalog—an AI metadata system and policy layer for data and AI in the Lakehouse. This goal is broken down in sub-goals, where the first one focuses on Automating the Minimization of Sensitive Data. The importance of Data Governance for the successful use of data in the organizations raises the need of demonstrating the Pixels approach in a real environment. More specifically, it is analyzed a subdomain of data governance, which is the automation of classification of sensitive data and privacy-aware access control across data and AI pipelines in production environments. The objective is to support the improved usability of AI solutions by providing mechanisms for applying suppression, transformation or masking when those sensitive dataset are used to train and/or in the inference phase of prediction/declaration. Then, it seeks to protect against possible leakage of PII information through AI systems.



8.2. Bias, Transparency, and Explainability in Governance Automation Governance automation for data ecosystems is not an end in itself, but should support the development of trustworthy AI systems. Automated classifiers, policy generation, and management workflows could amplify bias present in those founding elements. Bias in classifiers may lead to complete inaccuracy or unfair and undesirable business outcomes. The

impact of bias manifests across the full range of access and masking policies. Classifier results should therefore be reviewed at a suitable interval, with a full retest of all processes completed as required. Significantly attributed model decisions are flagged for human attention, and access policies for highly contributing users are assessed periodically. The governance capabilities are straightforward to audit and scrutinise. The known decision premises of both the control and audit algorithms are clear; manual inspecting the auxiliary models may be more time-consuming, but remains possible. Considerations of bias and the appropriate level of transparency are hallmarks of responsible AI systems. Automated decisions should be made transparent and explained to affected parties and principle stakeholders, particularly where the decisions shape the principal direction of the concerned AI service. An explainability capability is introduced during the design of the classifiers underpinning automating data-gov, with relevant alteration possible for different control models or auditor profiles.

9. Conclusion

Data minimization, anonymization, and pseudonymization are crucial for preventing unnecessary disclosure of personal identifiable information when accessing data for analysis or machine learning training. The proposal identifies techniques that achieve such protection regardless of the data consumer's use case, enabling supporting stakeholders, such as data controllers, to permit access without concern. Nevertheless, even with automated privacy-supporting techniques in place, considerable residual risks remain when training AI models. For such cases, safeguards can be applied at training or inference time to further mitigate leakage of sensitive information, although they may introduce biases. Proper auditing of AI systems and identifying leakage points are thus critical to avoiding persistence of such risk. The outlined automation ultimately supports data governance maturity and the establishment of data stewardship in organizations.

Automated data classification and policy-driven access control enable PII protection throughout the data lifecycle, and fusing result tables into established data pipelines guarantees the preservation of privacy. The three case studies demonstrate how automation, supported by tooling capabilities, minimizes the operational overhead usually associated with classification, access management, and privacy-preserving transformation. Automated labeling reduces the number of false negative access events in production AI systems, while end-to-end implementation of data lifecycle protection assures no PII exposure in the related data–AI pipelines. Ultimately, these examples contribute to the dynamic management of sensitive data, supporting the requirement for data minimization throughout analysis and learning processes.

Metric	Value	Context
Classification rules configured	19	Case Study I
Data objects automatically labeled	13,000	S3 buckets, Delta tables, and Azure SQL data assets
Sensitive cloud services with generated policies	4	Instance-level and column-masking policies
Users accessing sensitive data	132	Observed over the monitoring period
Business units involved	25	Observed over the monitoring period
Cloud services accessed	6	Observed over the monitoring period
Monitoring duration	8 days	Case Study I
Interactions matching expected pattern	63%	Sensitive-data usage aligned with expected behavior
AI pipeline stages covered	3	Training, evaluation, inference
Delta tables labeled in training-time protection	2	Case Study II
Workflow components	3	Case Study II architecture

Cloud services in end-to-end workflow	3	Case Study II architecture

Table : Explicit quantitative values mentioned in the article

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