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Chapter 9: Data Governance, Security, and Trust at Scale

9.1. Introduction

Data governance, security, and trust frameworks play a critical role in enabling the ethical, legal, and purposeful use of data at scale. Real-world examples show that violations can severely damage enterprise reputations and impact consumer welfare. Key principles of data governance, security, compliance, and trust at scale are identified, as well as recommendations for technology and organizational patterns that can help ensure effective implementation.

Three architectural principles influence the governance of all data in an organization's ecosystem: distributed ownership, built-in capabilities, and explicitness. The need for integrated metadata and data quality management and operational workflows is emphasized, as is the minimization of the chance of error and inadvertent malicious behavior. Assurance through comprehensive auditing and continuous risk assessment is essential for stakeholders to consider an organization's data, and the ensuing decisions and actions, trustworthy.

9.1.1. Scope and Objective

A complex, large-scale data ecosystem—such as the Internet of Things or a smart city—exposes data from disparate sources to a range of users, including external, autonomous, machine-to-machine applications and services. Such an environment presents not only new opportunities, but also a unique set of challenges. A vast array of actors can potentially access the data; hence, data quality and security can be compromised, and trust in the data can be eroded—all while regulatory compliance remains a legal requirement. Although technologies exist to address these challenges, governance defines the structure, roles, policies, and processes that help organizations to build, maintain, and operate these IT systems effectively at scale.

The discussion focuses on the establishment and operation of data governance, security, quality, and access in a large-scale complex data ecosystem. Key design and architectural considerations from the point of view of governance at scale are also highlighted. Although the results have been developed in the context of complex data lakes, they are applicable to any data environment of significant scale—whether public- or private-sector, technological or institutional, local or global.

Fig 9.1: Data Governance, Security, and Trust at Scale

9.1.2. Research design

Contributing to the broad theme of Data Governance, Security, and Trust at Scale, this Research Project addresses the foundational pillars of governance for data at large scale, accompanied by a set of associated considerations and decisions that must be taken into account and aligned in order to create a secure and trusted environment for data and associated services supporting analytics, artificial intelligence (AI), machine learning (ML), and other activities involving the preparation, processing, acceptance, generation, and/or use of data. Data trusts, in their various forms, provide a mechanism to help establish governance, compliance, and accountability relationships for (a subset of) data involved in specific problems.

The proposed approach builds on General Data Protection Regulation (GDPR) requirements for accountability and risk-based compliance; principles of governance at scale that enable privacy-capture and privacy-preserving designs; a negligence

perspective on trustworthy-brands and trust-deficiency economies; and the concept of data trust. Addressed drivers and research questions include creating effective governance imperatives for trust and compliance in the use of big data, AI, and machine learning; establishing an appropriate balance between the aspirational potential of these domains and acceptable usage risk; achieving the optimum trade-off between privacy preservation and privacy capture; and providing robust, systematic, and repeatable ways of deploying large-scale processes that directly affect personal privacy.

9.2. Foundations of Data Governance

Data governance is the definition, assignment, and management of decision-making rights and responsibilities related to data to ensure appropriate behavior in the use of data in the organization. Data governance establishes the strategy, standards, and processes that enable other data and analytics disciplines, such as security and privacy, data quality, and data cataloging, to operate effectively.

Data governance at scale considers these same activities, but with the added dimension of dealing with large-scale data estates managed by multiple data engineering teams. Responsibility for data governance shifts from a small, central committee to many decentralized data stewards, enabled and guided by governance operating models, dedicated governance systems, and automation. Data governance at scale is, therefore, the synthesis of a governance framework suitable for large-scale data environments, combined with the organization and underpinning technology to achieve the outcome.

9.2.1. Principles of governance at scale

Establishing an effective governance framework at scale is underpinned by several key principles. These principles maintain a strong focus on execution and delivery of results using governance controls that are Light-touch and Agile. Operational governance demands a careful balance between guideline-driven specification and too- prescriptive definition.

Prioritizing automation is critical at scale. Continuous auditing uses policy-as-code to require compliance and flag non-compliance at all times, allowing staff to focus on remediation rather than discovery. Everything must be automated: for example, approval processes need to be concurrently scheduled with execution using policy-based, provable, reversible change management tooling. All audits must deliver actionable insights within 24 hours and occur automatically, without manual checking.

Equation 1: Data Governance Equation

$$DG = (P + S + C + Q) \times ADG = (P + S + C + Q) \times ADG = (P + S + C + Q) \times A$$

Where:

- DG = Data Governance effectiveness
- P = Policies
- S = Standards
- C = Compliance
- Q = Data Quality
- A = Adoption across organization

9.2.2. Definitions and scope

Data Governance at Scale encompasses a set of decisions and activities establishing a framework for managing and utilizing data in large data ecosystems. Data governance is concerned with the availability, usability, integrity, and security of enterprise data, both in a physical and a logical sense, while ensuring that data and associated data-handling processes conform to relevant regulations, are supported by corresponding assurance processes, and incorporate relevant quality and audit monitoring considerations throughout the data lifecycle. At large scale, data governance also requires choices regarding the authority, accountability, and auditability of these decisions; the severity and implications of violations; the ability to carry out clearly documented and constrained exceptions; and the degree to which rigorous governance can be maintained, delegated, and adapted into dynamic governance processes.

Within an academic context, data governance responsibilities must also serve the needs of traditional research conduct and reporting, including project-based data management and associated control and audit requirements. Further, as academic institutions are and increasingly serve as data brokers and conduits for infrastructure- and service-scale data use, both end-user and enterprise context needs now encompass legislated accountability for the proper sale, use, and retention of such data. The lessons and approaches reflected here therefore arise from the consideration of both large public-sector data ecosystems (such as the Australian National Data Asset Strategy and associated infrastructure developments) and large enterprise ecosystems that must deliver both the requirements of individual entities and withstand the scrutiny and negotiate the conformity demands of external data users both within and beyond Australia.

9.2.3. Principles of governance at scale

Governance principles applying to large-scale data environments are outlined using a trust-centric framework. Data governance at scale must accommodate the large number of data producers and consumers across data ecosystems; the diverse range of contexts in which data is created, shared, and used; the multitude of requirements for data use and the high volume of data produced. Effective data governance must in addition help build and maintain trust within a data ecosystem.

Modern data ecosystems typically range in size from multiple organizational units within a single organization to sharing across organizations and sectors, often including local-authority data. Governance models must address the mechanisms and organizations that establish and enforce accepted principles, policies, standards, and procedures for sharing data between producers and users; the social contracts that establish the rights, responsibilities, and liabilities of producers, custodians, and consumers; and the decision-making authority for adding, altering, and deleting data, metadata, and structural–technical components of the ecosystem.

Large data-sharing initiatives are inherently vulnerable to mistrust because of their use and combination of sensitive personal, commercial, and resource location data. Users seek confidentiality around sensitive data, whereas producers want to maintain their competitive advantage. Both want assurance that the data will be used only for the stated purpose and not shared with unauthorized users. Privacy breaches and the misuse of personal data have raised growing public concerns and distrust in the willingness, intent, and capabilities of authorities, organizations, and vendors to protect sensitive data. Awareness that data collected for one purpose may be used for unrelated services amplifies these concerns. Building trust requires at least transparency about the collection and use of data and a practical mechanism for providing feedback.

9.2.4. Roles and responsibilities

Effective data governance at scale varies according to the organizational context and available resources; however, a core set of roles and responsibilities should be evident within every governance framework. In all settings, the executive board must take responsibility for ensuring compliance with relevant laws and regulations, as well as for supporting the business's core data governance activities. In addition, there should be a governance council consisting of leaders with responsibility for the organization's major data domains or lines of business. Their members share information about initiatives that might affect other domains, identify conflicting strategic goals, and renegotiate priorities across domains. The individuals with these strategic roles are often described as data sponsors.

In large organizations, additional formalized roles are necessary to ensure that day-to-day activities comply with the abstraction. Stewards are typically appointed for the most important data domains. They are responsible for decision-making and accountability, including the creation, maintenance, and retirement of common definitions of business entities within their domains; new data sources, collections, and repositories; access rights to data stores; data quality management procedures; and monitoring compliance with data-sharing agreements both internal and external to the organization.

9.3. Security in Large-Scale Data Environments

The architecture of large-scale systems need not be heavy both on governance and on security. In practice, clusters and micro-services evolved to support scale tend to loosely couple responsibility for trust and risk management, with production workload isolation reducing the impact of system breaches and failures. The least creative aspect of these systems is security. In particular, gating access in order to protect data is a repeated engineering pattern that might benefit from algorithmic and model-driven approaches. As expressed by the phrase "if your data was not encrypted, it was not yours" (green 2017) plain data storage was never a valid option and security must continuously improve to respond to increasingly powerful adversaries.

9.2: Security in Large-Scale Data Environments

Security engineering for large-scale processing must embrace separation of duties around identity, access, and authorization, around encryption and data protection, and

around compliance. An identity and access management system must decouple scheduling and workload from data access, with continuous mining of the access context to inform decisions downstream or online. Static partitioning and redundant storage of encrypted records across geographical zones or administrative domains limits the risk of breached confidentiality. In addition, signature and encryption keys may rotate across a workload life-cycle. A Digital Rights Management capability can further protect intellectual property in a multi-tenant ecosystem.

Presence of judiciously selected private data drainage points would permit on-going collection of data that cannot be generated without resources and personnel, while a Data Loss Prevention system can protect against exfiltration. Data governance must maintain an on-going dialogue to revise protection levels across a risk map that evolves with technology, duty allocation, skills availability or deterioration and threat perception.

9.3.1. Architectural considerations

Robust Data Governance, Security, and Trust at Scale – a tried, tested and extensively used approach – are more crucial in large-scale data management environments than in traditional data management. To maintain any semblance of order, scale is implicit in government, enterprise, and organisational data environments. Data Governance, Security, and Trust at Scale are essential when different operational environments work together, enabling data sharing and allowing diverse environments from different organisations to collaborate in new and exciting ways.

In any environment, people expect their data to be safe and managed by competent teams who take care of its data governance and security. People also expect that their data will be used for the purpose intended, that it is of high quality, that it conforms to due process, and that they can have their say in how it is managed and used. These same expectations hold in large-scale management environments. However, extending such expectations to very large environments is also much harder, for governance and operational roles can no longer be based on close personal relationships. In a large-scale deployment, where data are used in an open and often automated way, without direct human sign-off, implicit and explicit scaling issues become critically important. In particular, it is impossible for a small group of functional-area data managers to oversee the access, data protection and security settings, support, compliance checking, and operational environment for every asset in every functional area. Data Governance, Security, and Trust at Scale need to therefore be considered as first principles or non-functional requirements that can be tested, operated and deployed within large-scale operational management environments.

9.3.2. Identity, access, and authorization

Management of user identities and control of user access to sensitive data are foundational security capabilities in large, data-intensive enterprises. Usual identity and access management (IAM) solutions enable consolidation of users, roles, groups and organizations in centralized identity repositories, providing a single system of record (SoR) for identity and role data. The SoR can be leveraged across a heterogeneous environment comprising on-premises systems, external services, and cloud-based applications. Federation across different IAM systems helps reuse identities, streams, policies and entitlements contained in a system without replicating them and the need to manage two copies.

However, in data-intensive enterprises, significant additional elements have to be taken into account to achieve effective control of data access. The increasing adoption of user identity for security context enrichment and user-behavior monitoring for risk-based authorization results in vast data stores owned and managed by security, fraud and risk teams. The growing use of shared service accounts to access data and run automated jobs for feeding analytic or data-science systems makes attribution of such accesses to individuals more difficult. Shared or public service accounts tend to suffer from weaker password policies, and logs of transactional activities often lack meaningful context, shortening the window within which malicious or erroneous actions could be correlated with user identities. In addition, many of the sensitive actions performed by those accounts are not user-correlated, severely limiting forensic analysis.

9.3.3. Encryption and data protection

Within a large-scale data landscape, data protection mechanisms reduce risk exposure when other layers of security cannot minimize exposure by properly implementing least privilege data access. An end-to-end encryption strategy should be an objective of any data platform, but given the need for efficient storage, data processing, and easy data sharing by automated or human actors, not all data will be encrypted all the time. All stored and transferred data should be encrypted, preferably with encryption keys controlled by the data producers and consumption as defined by the governance framework and enforced by the policy engine. Data that is encrypted at-the-end, i.e., inside the data use environment, provides the best resilience, as even authorized operators of the data use environment cannot access the plaintext. Encryption at-the-end may create challenges for some analytical tasks that rely on performing calculations on the ciphertext. Such algorithms should be made available to the data producers and data use environment operators prior to any data sharing and be applied to the data custodians and data use environment providers upon receipt. RDMA APIs of storage systems that

transparently read the ciphertext and apply the encryption algorithms may help address performance concerns.

Intrusion detection systems, process monitoring systems, formal verification systems, and other systems that work at a scale require operational data at the same scale and cadence. Access controls, therefore, tend to be policy-driven based on least privilege to run those systems rather than risk-based on data sensitivity. However, admitting such data sources into a least-privilege scheme within the data use environment helps in providing learning data for AI systems that traditionally have used separate data silos. One such category is malware detection within an organization. Traffic data of HTTP and HTTPS GET methods are being prepared for unsupervised machine learning to detect accesses to known malicious domains. A separate data domain catering to intrusion detection systems will reduce the quality of the learning data.

9.4. Trust, Compliance, and Accountability

Field operations are trusted by design: security requirements and their compliance as well as data access authorizations can be assessed from formalized trust frameworks and their assurances. In turn, regulatory requirements and the allocation of compliance obligations are explicitly observable. Such a structured approach highly contributes to retaining tacitly trustable federated research environments. Expanding beyond pure regulatory compliance, the systematic considerations of compliance and risk management enhance trustworthiness along the operation and throughout the lifecycle into the next evolution of the governed environment as well as throughout supported surround and address decommission and land-utilization. Compliance is further ensured through logged orchestration allowing the independent audit, monitoring, forensics and traceability of flowed data including data-transmission provenance.

Trust and compliance encompass all above aspects, spanning early design phases involving all actors related to a federated research environment till operationalization of full-fledged monitoring, forensics and audit orchestrating the traceability of exercised obligations and generated data. In relation to trust frameworks, trust-enabling governance domains address data lineage, data quality, expressiveness of the contractual regime and auditing, with the last one covering issues related to data sharing and data use. Fully audit-compliant chain-of-custody detection, origin tracing and field provenance are enabled through monitoring of asset movement, transitions into utilization or storage, application of information security activities, operational policy compliance and enterprise system interfacing.

Trust and compliance issue domain for field-operation environments, and for contexts being organically extended by living-control and risk-of-use monitoring, thus adopt a

holistic view on regulatory requirements, allocation of compliance obligations and trust enabled by guarantees and assurance of applicable trust frameworks.

Equation 2: Data Security Equation

$$DS = (E + I + M + R) - VDS = (E + I + M + R) - VDS = (E + I + M + R) - V$$

Where:

- DS = Data Security strength
- E = Encryption
- I = Identity & Access Control
- M = Monitoring & Detection
- R = Response capability
- V = Vulnerabilities

9.4.1. Trust frameworks and assurance

While it is often difficult to define, trust is critical for data sharing and collaboration. Numerous data sharing frameworks have been developed for many sectors, nations, and between nations. These frameworks may address specific sectors across nation boundaries, e.g., the health sector. At a higher level, trust frameworks establish an ecosystem enabling interoperable, mutually trustworthy identity, credentials, and attribute solutions. The level of trust for a given application influences identity, access, verification, and data-sharing decisions. Trust frameworks must consider the protection of privacy and the disclosure of personal information, especially the purpose for which the data is shared and how it will be used, shared, managed, and subsequently stored or destroyed.

Trust frameworks generally do not specify or apply technologies but enable the necessary localized technology implementations and operating practices required to build, establish, and maintain mutual trust within the framework. They expand the typically limited set of trust relationships (e.g., between a hospital and the insurance provider) into a broader and reusable set across many organizations. Solutions operating in the trust framework ecosystem use those relationships to provide a specific set of functionality (access control, for example) that supports a broader operating need (sharing data across the nation for population health purposes).

9.4.2. Regulatory compliance and risk management

Compliance with laws, regulations, and other guiding principles is an essential part of data governance. Common regulatory requirements include the General Data Protection Regulation (GDPR) in Europe, the Federal Information Security Modernization Act (FISMA) in the US, the Health Insurance Portability and Accountability Act (HIPAA), and the Payment Card Industry Data Security Standard (PCI DSS) for payment systems. Industry standards such as SOC2 and ISO 27001 are similarly important.

The relevant laws and standards depend on the location of a company's headquarters and the processes it is executing. For instance, an organization mature enough to field an autonomous AI may nevertheless lack GDPR oversight for its automobile business if its headquarters are in Asia and the deployment area is the United States. Different countries and industries define specific risks and prescribe detailed actions to mitigate those risks. A bank operating in Europe is responsible for having the right cybersecurity controls in place, since the increased financial risk for customers relates to the cybersecurity of the bank, rather than that of the hospital. However, the information security community is aligned on patterns of risk that should be mitigated. For large-scale data collection—especially for large-language models—an organization that wishes to mitigate risk for data collection or also avoid reputational damage would typically cross-check the information-security checklists against potential violations of the guiding principles against which society expects these modes of data collection to be governed. These principles are ultimately defined by laws, which in turn originate from society itself.

9.4.3. Auditing, provenance, and explainability

Decisions about managing, sharing, and using data carry built-in risks. The absence of appropriate confidence can degrade data access and credibility, enabling events such as Cambridge Analytica scandal. How do existing compliance frameworks address these topics and what else is needed to provide sufficient trust? Ensuring adequate security is an essential enabler. It provides a level of guarantee that constrains the risk of data loss, corruption, or unauthorized usage, so that a data set can be shared or made available for usage without having to go through time-consuming and expensive re-evaluation every time someone wants to make use of it. This is a matter of engineering focused on ensuring certain security properties are satisfied for a specific data-enabling system and its broader environment. The next sub-section therefore examines auditing and compliance in more depth.

Auditing captures a record of what happened in a system, while provenance takes it further back to trace where data values come from, how they were derived, what processing flows operated on it, etc. Both play a critical role in enabling organizations

to ascertain whether these events or the flow of sensitive data actually respected the conditions of the trust framework. Ensuring that sensitive information is not being exploited inappropriately is the fundamental role of auditing; organizations want to be sure that classification labels are being respected. It assumes particular relevance when exploring pipelines for producing analytic results available to the public, as they must not produce undesired leaks. Popular models for expressing such data-flows information include Directed Acyclic Graphs and Data Delivery Diagrams. Concerns about data quality and trust in analytic results highlighted the need for consideration of the entire cycle: data generation, processing, and consumption.

9.5. Data Quality and Access at Scale

Data quality and access are interrelated aspects of governance that can be considered together. Poor data quality impedes usability, which limits access for those in the organization who need the data but lack intimacy with its underlying properties, such a quality—and, more importantly, the context of its creation and evolution—that only specialist curators can reasonably provide. Conversely, access control mechanisms impose demands on data quality: data must be either sufficient interoperable, so that disparate systems can reason about them relatively faultlessly, or sufficiently self-describing, so that irrelevant properties and variables can be ignored or masked.

Fig 9.3: Data Quality and Access at Scale

At scale, the history of a record is just as important as the record itself. Metadata—and especially metadata describing data lineage—underpins all other aspects of governance, and its collection must be mandated, automated, and woven into the use of data. A

metadata catalog summarizing and describing data assets and incorporating lineage information is a prerequisite for meeting the requirements of data quality, provenance, and access control. Such a catalog must be supported by user-driven data quality metrics and governance workflows that can drive remediation.

In building an organization's first data catalog, scalability is not the primary concern. What really matters is shaping the organization's data culture and putting the foundation services in place to enable data access, data quality, and enforcement of data policies through automated mechanisms. Access control remains critically important but is driven by stakeholder demand for permitted access to new assets. However, as catalogs mature and become trusted, demand tends to grow. At maturity, therefore, incorporating elements of privacy by design becomes essential for maintaining the balance of control without prohibiting access to data that is otherwise trusted and duly maintained.

9.5.1. Metadata management and data lineage

Governance of Large-Scale Systems Requires New Structures and Procedures

Governance of large-scale data ecosystems requires a focus on the usability, availability, and quality of the data available to data scientists and analysts. Metadata management, capture of data provenance, and the implementation of technological and human-centric data quality workflows are critical enablers in these areas.

Metadata Management and Data Lineage

Data catalogs are critical enablers for ensuring the quality and usability of the growing volume of data that is available in large-scale data ecosystems. Data catalogs are meta-database systems designed to store, manage, and curate knowledge about data assets. Data catalogs provide the ability to search, discover, and query cataloged data through a simple and consistent interface, typically using natural-language-based search terms. Using data catalogs, organizations can inventory their analytics assets—including datasets, models, reports, dashboards, and analytical applications—and facilitate robust data governance programs. Data catalogs serve as the authoritative inventory of data assets and enable effective collaboration among data consumers and producers. Data catalogs provide a single view of trusted data sources in the organization while also surfacing data quality metrics so that consumers can make informed decisions when using data in their analysis and algorithms. Key enablers for the value realization of data catalogs include continual curation of their contents, population of technical and business glossaries, and assignment of stewardship roles to govern and provide oversight for specific insights and data domains.

In a cloud-based data ecosystem, the cloud service provider manages the hardware, storage, and network management, enabling DataOps teams to focus on products and services rather than how to implement the infrastructure. Hence, Cloud DataOps teams can implement modern data strategies and uncover hidden opportunities for future growth. DataOps is a collaborative data management practice aimed at improving the quality and reducing the cycle time of data analytics. DataOps processes focus on improving deployment frequency and accelerating mean time to detect and correct corruptions and delays in data pipelines while fostering close collaboration between data engineers and other DataOps team members.

9.5.2. Data quality metrics and governance workflows

Developing workflow governance across an organization that collects, prepares, and stores shared data is crucial for managing quality. The approach enables production teams to track metrics associated with a data asset across their dependencies and leverage those insights to inform their consumers.

Data quality management processes can be established in numerous internal and external ways. Internal processes help monitor data quality across a company's shared datasets. An individual or group may propose data quality metrics in conjunction with a data quality steward in the data governance council, or in an independent quality assurance group. With appropriate disciplinary knowledge of the relevant datasets, the discussion would then flow to the broader internal data engineering community, where main dependencies can provide additional context on new or modified dependencies. Assessment input by these teams, particularly around detection thresholds, is crucial for a successful feedback loop.

External processes allow consumers of data assets use quality metrics to inform their acceptance criteria. Sufficient, precise quality information needs to be maintained for each asset, and covered assets need commitment from the producing team to act on relevant feedback. Such processes naturally extend to publishing data assets for external purposes.

An open-source organization provides an excellent case study: numerous projects combine to provide data that is used in various analyses and services, and quality issues are regularly uncovered. Internal civil engineering-related warnings have led to fixing issues with weather service data that is used by other projects, and with precipitation data from the OpenStreetMap project. The WARN ecosystem captures this feedback ultimately in a publicly visible routing table.

9.5.3.Access control, data masking, and privacy by design

An ecosystem of diverse actors generates and consumes large-scale data, including governmental, commercial, and research organizations. As these actors share and make data publicly accessible, they also need to protect sensitive information—such as personal data or business secrets. Typical solutions, including access control for read operations, are often insufficient to guarantee the privacy of released data when functions beyond simple read are considered and operationalized at scale. Masks remove certain sensitive aspects of the data; yet masking mechanisms tailored to a learning process (for instance a neural network) are rarely implemented at the probe or shared data levels. Various categories of privacy concerns need to be taken into account when sharing data. The alignment of participants' risk and privacy objectives with market incentives, using evaluations and mechanisms based on various kinds of data anonymity, remains a hot topic of investigation. Privacy by design, the integration of privacy-related and other technologies in the data life cycle, and subsequent auditing capabilities are among the major privacy-oriented security design patterns.

Large-scale data management introduces additional privacy-related concerns—such as the need for data protection guarantees in shared data management setups, with the concomitant unavailability of protecting releases enabling direct privacy guarantees. The use of cyber insurance for compensating leakage is being discussed. Markets for private information, aiming to leave control of personal data to people rather than companies, are in their infancy; alignement with sharing economy principles is for the moment restricted to a few start-ups. The establishment of procedural guarantees, substantiated by a third party, seems to constitute the most effective business model for the success of systems enabling data sharing and processing using those technologies. That is, making agreements on the host of the data should include the maximization of the use of the information for both parties within the roles assumed.

9.6. Technological Enablers for Scale

Technological developments shape Data Governance, Security, Compliance, and Trust (GSCT) not only by providing new modalities for data management, sharing, and usage but also by creating new sources of risk or introducing new requirements. Consequently, technological solutions can ensure that the principles and requirements of sound GSCT are followed at scale, enhancing the value of data ecosystems, and develop in compliance with the principles of the underlying GSCT. Three areas are particularly instrumental—Data Cataloging, Data Stewardship, and Security Engineering.

Data Cataloging and Stewardship Platforms. Cataloging and stewardship platforms that fulfill the needs of data producers, curators, and users form the backbone of scale.

Catalogs serving only metadata discovery and search are not sufficient. The catalog must also support the process workflows, notifications, and communications that facilitate collaboration among data producers, curators, and users. In particular, governing the access to sensitive data requires a close collaboration between data stewards and users, often involving data masking, user credentials issued by the data owner, or combinations thereof. Orchestration of these workflows is therefore essential. Bradford et al. 2020 advocate for a broad concept for such data cataloging and stewardship platforms that includes data cataloging, data quality, rights and access control, and membership management. Technical tooling such as catalog and data quality authoring tools work together to offer a rich functionality set for cataloging at scale. Security Engineering Patterns for Scalable Systems. Security engineering patterns for scalable systems, including those managed by many contributing stakeholders, provide reusable architectural wisdom for AI solutions. Patterns offer guidance on problematic aspects, such as incident management and monitoring of complex workflows or steering and control provisions across multiple "possibly-purposive actors." The patterns also help meet diverse security objectives while retaining a natural balance between usability and security.

Equation 3: Trust at Scale Equation

$$T = (G + S + Tr + Ex)UT = \frac{(G + S + Tr + Ex)}{U} T = U(G + S + Tr + Ex)$$

Where:

- T = Trust
- G = Governance maturity
- S = Security reliability
- Tr = Transparency
- Ex = User Experience
- U = Uncertainty (risk, bias, inconsistency)

9.6.1. Data cataloging and stewardship platforms

A growing number of organizations are deploying data cataloging solutions to assist with data discovery, stewardship, classification, and compliance management. Such systems can leverage internal and external sources of metadata and support business glossaries, auditing of delegated cataloging activities, and also integration with data quality tools.

Enterprise data stewarding platforms, such as Informatica's Enterprise Information Catalog, allow organizations to leverage machine-learning technologies to classify data en masse by inferring sensitive attributes and message content.

Public cloud providers offer managed services to assist with monitoring and remediating compliance posture across data in their platforms: Azure Purview, AWS Macie, and Google Cloud DLP. These services support data discovery and classification as well as risk modeling and alerting. Moreover, services that support other aspects of data governance, such as Dataiku and Trifacta, are beginning to include automated compliance assistance.

9.6.2. Security engineering patterns for scalable systems

Central to any approach to security in highly developed systems is the concept of defence in depth, which consists of a strategy for multilayered protection against malicious threats. Security throughout a system’s lifecycle requires the harmonious collaboration of distinct roles, processes, and technologies. Implementation patterns derived from classical ratios, in especially threat modelling, allow for focused activities across layers of the architecture. These templates are complemented by patterns pertaining to aspects of a security system at large, including authentication, authorisation, encryption, auditing, security of servers and support processes, and incident management.

Enterprise-scale systems, comprising hundreds or thousands of servers, face vastly increased demands for acceptable service, resiliency, and security versus design, construction, and operational effort. Architectural innovation for these systems produces new problems that are not addressed by classical security ratios and require other design, operational, cultural, and technology responses. For example, the need to authenticate and authorise users at large scales lends volume and management complexity and hence cost to authentication infrastructures; the relatively low cost of individual units of capacity drives system developers to curate community engagements in the hope of absorbing malicious activities; the volume of incoming alerts from security monitoring often creates alert fatigue that dulls sensitivity to real incidents.

Dispersal across multiple technology domains raises the significance of security servicing links—for example, between Web applications and underlying data sources, services, and processing logic. A well-controlled Web surface layer is essential, but is often mistakenly viewed as the complete defence solution; it is only the minimum security service provision expected of the internal support domains, and only effective if the Web layer is correctly integrated with the other security services, including those of application services not exposed externally—client-side controls and checks in the customer environment; the design of local resource retrieval channels; the risk inherent in secondary usage of recognised connections, particularly to internal services of the business domain's "peer" security domains; and the security of operational processes.

9.6.3. automation, orchestration, and policy enforcement

Automation, orchestration, and policy enforcement are vital enablers for achieving the governance, security, and trust objectives detailed above at scale, considering the breadth and complexity of large-scale data ecosystems. Data governance and security need to work seamlessly together to ensure that processes for discovery and consumption of data satisfy security, privacy, and compliance requirements. Since these requirements vary across datasets from distinct sources in different geographical jurisdictions, distinctive policies need to be defined for dissimilar datasets sharing the same underlying infrastructure and orchestrated end-to-end.

The policies should address all aspects of the end-to-end data lifecycle including, data ingests, custodianship, dynamic protection of data in storage and during processing, quality assessment during processing, access, sharing, and serving. Approval procedures involved in sensitive processes should also be automated and based on underlying security and privacy policies. If data flows traverse under different authorities, provenance needs to be traced unambiguously. Ideally the authorisation procedures should handle bypassing the flow through the broker and follow end-to-end encryption patterns where specifically needed. Orchestration frameworks providing support for imperative and declarative policy definitions can significantly simplify the task of both engineering and operations teams creating automatable workflows.

9.7. Conclusion

As more organizations are increasingly coming to recognize the necessity of managing those data assets that have historically been thought of merely as by-products of business operations—a step regarded as the first stage of true “data maturity”—effective data governance practices are emerging. Governance at such scale, by integrating elements of security, trust, quality, and compliance, establishes the foundation for leveraging data at scale and with the anticipated benefits. The interplay among these different elements is increasingly under focus, together with the need for solutions that provide an integrated approach across elements in a single environment.

At the same time, advances in technology enable the analysis and exploitation of massive data sets, including extremely sensitive data sets, as never before. As organizations seek not just to gather and exploit more data but also to make those data sources available to third parties and external services, with the knowledge and consent of the data-participants, the need for provable airtight security becomes paramount. Organizations and Cloud Service Providers (CSPs) must pursue and implement robust data governance solutions that integrate security, trust, compliance, quality, and assurance to meet these conflicting demands.

9.7.1. Emerging Trends

The industry is witnessing a number of major trends impacting the domains of governance, compliance, security, and quality—addressing key questions about how data should be acquired, used, and protected and the trade-offs involved. Data governance is trending toward greater decentralization of decision-making, seeking to empower domains closer to the data while preserving company-wide standards. New democratization strategies focus on participation rather than just providing self-service tools. Compliance teams are facilitating regulations like GDPR rather than serving only as a control function. Security is evolving from detection and protection to a focus on prevention, with exposure management at its center. Continuous compliance processes help proactively avoid gaps that lead to serious breaches. Data quality teams are embracing a risk-based approach that recognizes some use cases—especially those feeding analytical models—as more sensitive than others and therefore requiring stricter quality controls.

The emergence of a digital native company model is finally driving investment in foundational components around data. Data catalogs, foundation models, and provenance-aware data pipelines are becoming the first investments in many organizations' data strategies. The DataMesh paradigm is being evaluated as a strategy to govern enterprise data in a federated manner as a product while maintaining a logical central control and accountability of the data assets. The automation of security engineering patterns for cloud-based and data-centric applications is supporting both the design and the operation of large-scale systems with security as an intrinsic property..

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