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Data Mesh Architecture for Decentralized Fraud Detection in Large Enterprises

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Abstract:

The increasing complexity of fraud in large enterprises, particularly in financial and transactional ecosystems, necessitates a scalable, agile, and distributed detection approach. Traditional centralized fraud detection architectures struggle to keep pace with the real-time requirements, data silos, and domain-specific fraud patterns that arise across organizational units. This paper explores the application of Data Mesh architecture as a decentralized and domain-oriented paradigm for enhancing fraud detection in large enterprises. Data Mesh shifts the ownership of data from centralized teams to domain-specific teams, treating data as a product and enabling better scalability, autonomy, and responsiveness.

We propose a Data Mesh-based fraud detection model wherein each business domain—such as sales, finance, customer relations, and operations—operates as a semi-autonomous node capable of detecting fraud patterns locally while contributing to an enterprise-wide fraud intelligence network. Leveraging a federated governance model, the architecture facilitates standardized yet decentralized policy enforcement, model deployment, and cross-domain collaboration. This paper examines how data product thinking, domain-driven design, self-serve data platforms, and federated computational governance work together to create a resilient and adaptable architecture for fraud detection.

The proposed methodology utilizes distributed anomaly detection algorithms, local event-driven stream processing (e.g., Apache Kafka and Flink), and inter-domain feedback loops for continuous model retraining and behavior correlation. Experimental simulations conducted on synthetic multi-domain enterprise data reveal improved time-to-detection, reduced false positives, and enhanced fraud detection in low-signal data scenarios compared to centralized models. Furthermore, the architecture demonstrates superior scalability and flexibility when integrating new domains and updating detection logic.

The findings of this research indicate that Data Mesh not only democratizes access to fraud-related data but also enhances detection capabilities by aligning technical solutions with organizational complexity. This paper contributes to the growing body of decentralized AI applications in enterprises and offers actionable design patterns for implementing domain-centric fraud analytics in large organizations. Future work includes extending this architecture to incorporate privacy-preserving technologies such as federated learning and exploring its applicability in regulatory compliance frameworks.

Keywords: Data Mesh, Decentralized Architecture, Fraud Detection, Large Enterprises, Domain-Driven Design, Data Products, Federated Governance, Anomaly Detection, Event Stream Processing, Self-Serve Data Platforms, Apache Kafka, Real-Time Analytics, Microservices Architecture, Distributed Data Ownership, Enterprise Data Fabric.

I. INTRODUCTION

Fraud remains a pressing issue for many large organizations, particularly those in highly regulated and transaction-intensive fields such as banking, insurance, retail, and telecommunications. As organizations become increasingly complex, with numerous processes spread geographically across diverse regions,

traditional monolithic or centralized fraud detection methods will no longer be sufficient. These comprise data latency, inability to scale, stove-piped intelligence, and the inability to customize fraud models to the specific attributes of individual business domains. Typically, centralized architectures utilize centralized data lakes or data warehouses, which can result in bottlenecks during the ingestion, transformation, and contextualization of data. In the era of developing sophisticated fraud vectors and increasingly complex attack strategies, companies require a decentralized, adaptable, and responsive architecture tailored to the modern data ecosystem.

This paper presents the concept of a Data Mesh architecture as a potential solution for decentralizing fraud detection in large organizations. Introduced by Zhamak Dehghani in 2019, Data Mesh emphasizes decoupling centralized data architectures to center around a decentralized domain-oriented data ownership and architecture. It focuses on treating data as a product, using self-service infrastructure platforms, and enabling federated computational governance. The plurality case is a fatal flaw; however, it places the responsibility for, and power to manage, their data in the business units, and opens the floodgates to the business's growth of analytics and operational insights without becoming reliant on a centralized data-engineering team. This is particularly advantageous in the context of fraud detection, where context-based learning methods and proximity to data events are important for accurately and timely identification of fraudulent observations.

Old school with fraud detection systems that need to move data to a central point to apply rules / ML models. This practice not only accumulates delays by failing to detect malicious activity but also often lacks the contextual evidence that industry-specific experts require to make informed decisions. Additionally, a one-size-fits-all model generally does not work well across different domains with significantly varied transactional behavioral patterns, regulatory compliance requirements, and fraud signals. Data Mesh enables the localisation of fraud detection capabilities to each specific domain, allowing them to create, deploy, and iterate on models based on their unique patterns, all while contributing to the collective intelligence of the enterprise.

However, as data becomes increasingly distributed—placed in microservices, on different cloud platforms, and on edge systems—so too do analytics and machine-learning capabilities need to be developed to derive insights from it. Data Mesh neatly complements this distributed setting by allowing smaller, well-defined domains, such as "customer_service", "billing", "logistics", and "finance", to own their own "fraud data products". These are trusted, standardized data sets available through APIs that can be hosted and made available to fraud analytics in real-time or near real-time. Cross-domain interoperability is enabled through federated governance policies that define global best practices, such as data quality and model auditing, and ensure the secure utilization of models in a manner that does not compromise domain sovereignty.

The value proposition of using Data Mesh for Fraud Detection centers around the idea of speeding up the time to detect fraud, decreasing the number of false positives by utilizing domain-specific smarts, and encouraging cross-functional partnerships. It also promotes a culture of data accountability and responsibility, encouraging domains to work to enhance the quality and value of their data. This paper presents the implementation of a decentralized fraud detection system, utilizing simulation-based results, and offers guidelines for pragmatic deployment in large corporations.

Next, we provide a detailed review of related works, the Data Mesh principles, the methodology for performing decentralized fraud detection using domain-aligned data products, the results of experiments conducted in a simulated real enterprise setting, and an analysis of scalability, performance, and applicability. With Data Mesh, architectural design and organizational structure are brought into synchronization, and it also offers a more intelligent and flexible way to fraud prevention in today's enterprises.

II. LITERATURE REVIEW

The ever-changing methods of fraud, however, have challenged the scalability and flexibility of centralized fraud detection architectures. These systems have issues with latency, inflexibility, and a lack of context when functioning across large, multi-domain enterprises. Several research works have highlighted the drawbacks of monolithic detection systems and the need to shift towards domain-aware and distributed analytics

solutions. This review covers the fundamentals of Data Mesh, the evolution of fraud detection systems, and the emerging technologies that enable a decentralized data and analytics infrastructure.

Dehghani \ first introduced the concept of Data Mesh cite{1}, where he advocated for data treated as a product and distributed data ownership through domain-driven design. Her framework proposes four fundamental principles: domain-specific decentralized data ownership and architecture, data as a product, self-serve data infrastructure, and federated computational governance. This vision aligns perfectly with large organizations, where disparate operational areas—finance, sales, HR, and operations— operate semi-autonomously but serve to realize enterprise objectives. The migration of fraud detection methodologies in such a federated data ecosystem has been recently studied, particularly from an agile and context-aware perspective.

The early systems for detecting fraud were primarily based on rule-based systems, which were easy to implement but resulted in high proportions of false positives and were inflexible to changes [2]. As the volume of transactional data increased, data mining approaches such as machine learning were developed to improve pattern finding and anomaly detection. Legacy ML Tools, such as supervised classification and unsupervised clustering, would generally collect data back at a warehouse for training and scoring models [3]. However, such centralization introduces delays, governance risks, and rigidity in terms of domain-specific contextual modeling.

More recently, studies have shifted to investigate more distributed and real-time methods. Indeed, real-time streaming fraud detection on Apache Kafka and Apache Flink [4] has demonstrated the ability to reduce fraud detection time and enhance responsiveness significantly. These platforms enable event-driven architectures, allowing fraud signals to be processed at the time of detection, leading to real-time domain ownership, as the Data Mesh principle states. In parallel, the concept of microservices has also been explored for fraud analytics by Lin et al. [5], who demonstrated how components for fraud detection can be scaled independently and function in localized data ecosystems.

The rising focus on data sovereignty and regulatory compliance, including the GDPR globally and India's DPDP Bill, also mandates decentralized processes. One potential solution is to apply federated learning, which would enable training fraud detection models across decentralized data sources without requiring the physical merging of the data [6]. This approach is also compatible with the Data Mesh paradigm, in which each domain can participate in a global fraud model while retaining ownership of its data.

In an enterprise setting, Data Mesh is gaining traction, particularly in companies with established DevOps and domain-driven cultures. For example, Zalando shared their experience in developing domain-focused data products for a fraud analytics use case [7]. Their case illustrates a need for clarification concerning product ownership, SLAs related to data quality, and interoperable schemas for cross-domain analytics. Also, ThoughtWorks has promoted Data Mesh as a foundational component of contemporary data platforms, highlighting its scalability requirements for big and complex enterprises [8].

Despite its potential, the utilization of Data Mesh for fraud detection is not well-studied, especially in the operationalization of decentralized anomaly detection algorithms and in ensuring uniform governance across domains. This lack of an in-depth study is the motivation for this paper, which introduces a concrete architecture and evaluates it in a simulated large-scale environment. The literature review highlights the shortcomings of centralized systems and advocates for decentralized, domain-aware models that are enabled by Data Mesh principles.

III. METHODOLOGY

Develop a data mesh architecture for decentralized fraud detection and prevention. In this work, we propose a multi-phase approach that includes architectural design, data model design, simulation environment construction, and performance comparison of the data mesh. The goal is to model a domain-driven environment in which each operational unit remains autonomous while participating through federated governance and shared intelligence in fraud detection. The approach ensures adherence to the four tenets of

Data Mesh – domain-oriented ownership, data as a product, self-serve infrastructure, and federated governance – while building in real-time, localized fraud monitoring.

The first stage in this three-part process breaks a big business into operational domains that often encounter fraud situations. These domains typically include payments, customer onboarding, product returns, internal purchasing, and third-party logistics. To abstract fraud detection at scale into a manageable problem, Facebook divides the massive scale of fraud detection into a set of domains, each of which is responsible for managing its own data products, fraud rules, and detection models. These data products are versioned, cataloged, and served through APIs using a self-serve data platform powered by Apache Kafka for real-time data sharing and Apache Iceberg for immutable data versioning—a single data catalog, such as Amundsen or DataHub, stores metadata for each data product.

This second stage relates to the deployment of domain-centric fraud detection algorithms. If applicable, according to the data in the domain, supervised learning models, including decision trees, logistic regression, and ensemble methods (e.g., Random Forest, XGBoost), are used. Isolation forests, clustering, and autoencoders are employed for domains with limited labeled data. Feature engineering happens within domains to extract context and reduce noise. Each model is trained and deployed separately in containerized environments (Docker), orchestrated by domain-level-driven Kubernetes clusters. The model is trained and retrained in the background through a CI/CD pipeline that utilizes domain-specific data versioning.

The third stage adds a federated governance layer for cross-domain cooperation, global fraud rule sharing, and model integration. This layer is managed by policy-as-code tools, such as OPA, which are in charge of access control, Data quality SLAs, and schema consistency enforcement within the data mesh. It also facilitates safe cross-domain flow of anonymized fraud signals. One fraud signal in a domain, such as recurring payment failures detected in the payment domain, can then be pushed to another domain (like customer service or logistics) through a Kafka topic named 'fraud-intel'. This cross-domain signaling is necessary for detecting coordinated fraud across multiple channels.

To mimic such architecture, synthetic datasets were generated for approximately five enterprise domains, comprising about 1 million records, in which fraud patterns were embedded with varying types, frequencies, and scales. Simulators created with fake unrolled facts, such as login, transaction, shipping, and refund, were used. We evaluate the performance of the models in terms of accuracy, false positive rate, training time, and time to detection under three deployment scenarios: centralized detection, siloed detection, and Data Mesh-based detection.

The final phase involved comparing the results, with a focus on scalability, modularity, fault tolerance, and governance efficiency. One focus was on the ability to detect fraud attempts across multiple domains—a blind spot of known magnitude in centralized systems. In addition, the influence of the decentralized model retraining on the system's ability to adapt to long-term drift in fraud patterns was evaluated through rolling time-window simulations.

This approach provides a guide for companies to set up and test decentralized fraud detection via a Data Mesh design. The strategy aims to strike a balance between agility, accuracy, and compliance by operationalizing domain-level fraud analytics and centralizing governance.

IV. RESULTS

The implementation and evaluation of the proposed Data Mesh-based decentralized fraud detection architecture yielded significant insights across accuracy, latency, scalability, and adaptability when compared to both centralized and siloed approaches. The simulation environment was set up using five enterprise domains—Payments, Onboarding, Returns, Logistics, and Vendor Management—each producing real-time transactional and event-based data streams. A total of five million synthetic records were generated, embedding both known and novel fraud patterns to test the models' ability to detect diverse fraudulent behaviors.

Across all domains, the decentralized architecture demonstrated superior detection accuracy and lower false positive rates compared to the centralized baseline. For instance, the Payment domain achieved an accuracy

of 94.3% with the decentralized approach, compared to 88.7% in the centralized model and 78.5% in isolated silo detection. Similarly, the Returns domain showed a reduction in false positives from 12.4% in the centralized model to 7.8% in the decentralized setup. This improvement was attributed to domain-specific feature engineering and localized model tuning, which allowed each domain to capture nuanced fraud behaviors without overgeneralization.

Another critical metric, Time to Detection (TTD), improved significantly. In centralized detection systems, TTD averaged 2.7 seconds due to batch aggregation and latency in data centralization. In contrast, the Data Mesh architecture reduced this to an average of 0.9 seconds, benefiting from near real-time event streaming and immediate domain-level inference. This metric is crucial in financial fraud prevention, where response time directly correlates with financial exposure.

Model retraining frequency and adaptability to fraud pattern drift were also evaluated. Each domain, when operating independently under a Data Mesh paradigm, was able to retrain models every 48–72 hours using domain-specific feedback and misclassification analysis. In comparison, the centralized model required a longer 10–14 day update cycle due to the overhead of complete data pipeline refreshes and centralized validation protocols. This agility enabled domains to respond more quickly to emerging fraud patterns, particularly in rapidly evolving areas such as Onboarding and Vendor Management.

Regarding cross-domain fraud detection, which is often a challenge in decentralized settings, the federated fraud intelligence channel (fraud-intel Kafka topic) proved to be highly effective in this regard. During the simulation, a coordinated fraud attack scenario spanning the Payments, Logistics, and Returns domains was correctly identified by the decentralized system, achieving a detection accuracy of 91.2%. In contrast, the centralized model flagged the behavior but failed to attribute it across domains with contextual correlation, resulting in only 74.6% accuracy.

From an infrastructure perspective, the decentralized architecture demonstrated better scalability. Each domain's data product and model container operated with isolated compute resources, reducing dependency conflicts and improving throughput during peak loads. Kubernetes orchestration ensured that each domain could scale its detection service horizontally without impacting others. The average CPU and memory usage remained under 60% utilization across domains, even under simulated surge conditions.

The implementation also revealed governance benefits. With the Open Policy Agent enforcing access control and quality rules at the domain level, no recorded data policy violations occurred during the simulation. This decentralized enforcement mechanism maintained compliance while enabling domain autonomy, a key pillar of Data Mesh.

The results affirm that a Data Mesh-based architecture not only enhances the technical performance of fraud detection systems but also introduces operational efficiencies and resilience. The improvements in detection accuracy, speed, scalability, and governance compliance indicate that such architectures are well-suited for large enterprises seeking to modernize their fraud mitigation strategies in a modular and future-proof manner.

V. DISCUSSION

The experimental results provide strong evidence that implementing a Data Mesh architecture in the fraud detection processes of large companies yields significant benefits compared to prevailing centralized and siloed paradigms. This section discusses the implications of these results in terms of architectural scalability, operational efficiency, organizational alignment, and future extensibility, further demonstrating that decentralized fraud detection strategies are feasible within the enterprise today.

Another notable finding is that both detection performance and time-to-detection are significantly enhanced in the case of the decentralized approach. This supports the assumption that fraud detection is more accurate if designed as domain-specific logic operating in the “narrow” context of each domain, catering to its specific transactional fine-grained behavior. This is a stark contrast to a central model that often relies on broad heuristics, which may not be aware of all domain-specific exceptions; in contrast, Data Mesh supports these exceptions natively. Every domain, considered a product team, is in the best position to identify and respond to the specific fraud scenarios that are unique to its own business. The consequence of this is a significant

reduction in false positives, especially for domains such as Returns and Logistics, where fraudulent activity is, in fact, "legitimate" but only without a specific domain context.

With time-to-detection now nearly three times faster, dropping latency from 2.7 to 0.9 seconds, the implications this has for enterprise security are significant. Immediate or near-immediate fraud response is not a nice-to-have, but a must in an environment where the financial impact can increase by the second. Through local stream processing and microservices, Data Mesh enables the agile discovery and fast reaction required by today's digital ecosystem at the location of data origination.

In addition, the federated governance layer not only ensures regulatory compliance and standardization across the domains but also supports a collaborative approach to fraud intelligence. The capability to publish anonymized fraud signals on Kafka topics, such as fraud-intel, mimics a federated fraud intel center within the company. This mechanism was effective at identifying coordinated fraud spanning multiple domains, an area where siloed or purely local models often fall short.

Self-serve data platforms also help increase developer velocity and enable fresher models. Each domain can retrain and deploy fraud models independently based on local drift signals, allowing the models to adapt more quickly without relying on a central data science or MLOps team. This decentralized model of lifecycle management is an excellent match for agile enterprise methodologies, helping to eliminate bottlenecks created by traditional change management processes.

Such advantages do not come without operational challenges with the Data Mesh model. Operating across those distributed pipelines, maintaining consistent observability across domains and even at the cluster level, and ensuring portability in fraud signal formats are not trivial challenges. We addressed these issues through standardized data product templates, schema registries, and federated policy enforcement in our simulation. However, real-world enterprise adoption would require a cultural shift in data ownership, investment in platform engineering, strong data product management, and more.

Furthermore, although the simulation-based evidence suggests the potential of this design system, its deployment in the field would necessitate comprehensive connections and authorizations to enterprise identity, access management, and security control systems. Finally, a mechanism is required to prevent cross-domain fraud signals from causing overfitting or increasing false positives in untargeted domains. This problem necessitates careful balancing of signal weights and probabilistic inference.

This exploration demonstrates that the Data Mesh architecture for fraud detection has a broader technical impact, while also showing how enterprises can frame their view on data and ownership, and redesign their approach to fraud mitigation. It is a game changer in that it shifts the focus from passive fraud defenses to intelligent, adaptive, and collaborative counter-fraud strategies that reflect the realities of 21st-century organizations and data.

VI. CONCLUSION

The landscape of enterprise fraud detection is rapidly evolving, demanding architectural paradigms that can adapt to the distributed, complex, and dynamic nature of modern organizations. This paper presented a comprehensive approach to implementing decentralized fraud detection using the principles of Data Mesh architecture. Through detailed methodology and simulation-based evaluation, we demonstrated that shifting from a centralized model to a domain-oriented, federated system significantly enhances detection accuracy, responsiveness, and adaptability.

The findings underscore the critical advantage of embedding fraud detection mechanisms within the operational fabric of each domain. Localized models, developed and maintained by domain-specific teams, proved to be more contextually aware and agile in responding to changes in fraud patterns. By treating data as a product, domains are empowered to ensure the quality, relevance, and timeliness of their own fraud data assets. This model promotes not only technical efficiency but also organizational accountability and domain-specific innovation.

The architecture’s reliance on event-driven platforms, such as Apache Kafka and Apache Flink, facilitated real-time processing and anomaly detection, significantly reducing the time-to-detection. This agility is

particularly vital in scenarios where swift action can prevent cascading financial and reputational damages. Moreover, the federated governance layer enabled domains to collaborate while maintaining autonomy, ensuring a unified fraud detection posture without compromising local control or regulatory compliance.

Equally important was the system's ability to detect cross-domain coordinated fraud attempts—a persistent weakness in both centralized and siloed architectures. The use of inter-domain signaling channels and shared fraud intelligence allowed the system to act holistically, correlating events and behaviors across domain boundaries without centralizing raw data. This balance between decentralization and coordination is a hallmark strength of the Data Mesh approach.

While the benefits are clear, implementing such a system is not without challenges. Enterprises must invest in cultural transformation to support decentralized data ownership, develop robust self-serve infrastructure, and establish effective federated governance practices. Tools for metadata management, lineage tracking, and automated compliance must be integrated seamlessly to ensure data quality and auditability across the mesh.

Future directions of this research include the real-world deployment in production systems and the integration of privacy-preserving technologies, such as federated learning and differential privacy, to further enhance data security. Additionally, the architecture can be extended to support real-time model monitoring, alerting, and explainability dashboards for fraud analysts, thereby improving transparency and trust in automated decisions.

Data Mesh offers a powerful and practical architecture for decentralizing fraud detection in large enterprises. It aligns technological innovation with organizational structure, enabling scalable, responsive, and intelligent fraud defense systems. As digital ecosystems continue to grow in complexity and interdependence, the adoption of such decentralized data paradigms will be essential for enterprises aiming to stay ahead of emerging fraud threats.

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