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Cloud-Native Big Data Architecture for Real-Time Tax Analytics, Fraud Detection, and Fiscal Governance

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ABSTRACT: Tax Analytics, fraud detection within tax systems, and governance are three areas where data is increasingly processed, thanks to the growing volume of tax records, payment transactions, company trades, and digital services and applications. Real-time processing engines allow continuous ingestion, detection of useful insights while data flows, and preparation of data-ready-to-query in analytical repositories. A novel modular architecture that fits the cloud-native paradigm and employs a mix of batch, micro-batch, and stream processing paradigms allows for a scalable and flexible solution. A monitoring framework allows the detection of problems in the flow and content of the data. The architecture addresses Governance, Compliance, Security, and Auditability aspects without letting these concerns become a bottleneck. The proposed architecture paves the way for a full-fledged implementation, as a clear roadmap emerges.

The Cloud-Native principles and the Elasticity, Loose Coupling, Service Orientation, and Microservices properties define how the solution must evolve. Modular and easily interchangeable components are favoured over monolithic architectures, offering flexibility and maintaining the costs for less frequently used modules in the investment background. The reference architecture, its components, the direction of the data flow and the Governance areas of concern are presented, together with the high-level design criteria and relative evaluation metrics.

KEYWORDS: Real time, data analytics, tax, fraud detection, cloud, architecture, tax, detection, detection, governance.

I. INTRODUCTION

Tax system design has social and economic importance, and tax analytics may improve tax growth and compliance levels. Significantly, tax fraud siphons off 10–15% of revenues in developing countries. Outsourced fraud detection is commercially viable but may offer firms rich insights. Therefore, a Big Data cloud-native architecture using a streaming approach can provide real-time tax analytics, support fraud detection, and assist governments in retaining control of the tax system. The architecture merges research and technological evidence; aligns with the technology risk-management framework; meets 44 cloud standards (security, privacy, business continuity, quality of service, data availability, and economy); and adheres to regulations.

The research's architectural principles and the principles governing data ingestion, storage, processing, fraud detection, governance, compliance, security, scalability, observability, and a case-management module guide its design. Subsequent sections examine the architecture in detail. Can architectural principles support a cloud-native Big Data architecture that allows real-time tax analytics, assists fraud detection, and retains fiscal governance? A cloud-native Big Data architecture enables rapid integration of third-party applications and services, supports various data-consumption paradigms, allows users to scale resources elastically, meets data-residency requirements, and enforces zero-trust security.

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Table 1: Core Components of Cloud-Native Tax Analytics Architecture

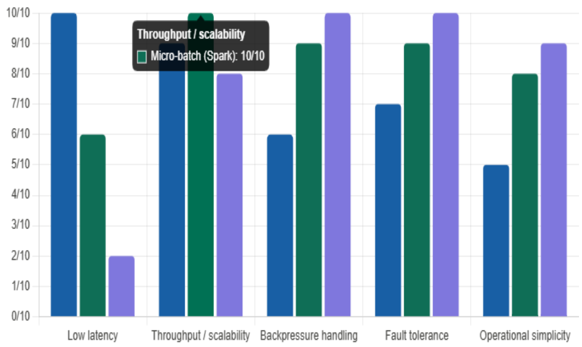
Component	Function	Technologies/Approach	Benefits
Data Ingestion Layer	Collects tax records and transaction streams	Apache Kafka, APIs, Log Streams	Real-time data acquisition
Stream Processing Engine	Processes live data streams	Apache Spark Streaming, Flink	Low-latency analytics
Data Storage Layer	Stores structured and unstructured data	Data Lake, Cloud Storage	Scalable storage
Fraud Detection Module	Detects anomalies and suspicious activities	ML Models, Clustering Algorithms	Early fraud identification
Governance Layer	Ensures compliance and auditing	RBAC, ABAC, DLP Policies	Secure data governance
Monitoring & Observability	Tracks performance and failures	Dashboards, Logs, Alerts	Improved reliability

II. ARCHITECTURAL PRINCIPLES FOR CLOUD-NATIVE REAL-TIME TAX ANALYTICS

Cloud-native computing empowers the development of on-demand software systems that instantiate only when needed and scale automatically to handle traffic surges. Using cloud-native principles, a reference architecture for tax systems supports scalable data ingestion and near-real-time analytics for tax policy, compliance, and fraud detection, all framed within a comprehensive governance blueprint. Three questions guide the discussion:

- Why should a cloud-native architecture for tax systems be favoured over a monolithic approach?
- What are the reference components of such an architecture, including dataflows and governance boundaries?
- What criteria should inform the architecture's design and evaluation?

Cloud-native applications leverage cloud elasticity and service-oriented design: software is modular and built from loosely coupled components. The decoupled microservice model resembles a fabric that readily integrates bespoke capabilities delivered by third parties, such as payment gateways, email servers, and Android or iOS proxies for mobile authentication. By contrast, monolithic systems are knitted from a single yarn. Cloud-native use cases, such as ride-hailing applications, rely on multiple microservices, not a monolithic solution.



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Processing paradigms comparison — a grouped bar chart contrasting stream processing, micro-batch (Apache Spark), and batch (Airflow) across dimensions like low latency, throughput, backpressure handling, and fault tolerance. Also displays the paper's SLA targets: alerts under 10 seconds, dashboard refresh under 60 seconds.

III. DATA INGESTION AND STREAMING FOR REAL-TIME INSIGHTS

Real-time insights from tax-related data require suitable ingestion, cleansing, enrichment, and quality controls. Data from multiple records, transactions, and logs should stream into a decentralized cloud-native platform, where they are cleaned, organized, and prepared for consumption. This section addresses ingestion sources, platforms, data-cleansing procedures, quality checks, and latency targets.

Tax records, transactions, and logs fuel real-time insights. Taxpayer profile updates, filings, receipts, refund requests, and responses to auditing data requests represent major sources. Ingestion aims for data-streaming platforms with appropriate schema evolution, backpressure handling, and at-least-once or exactly-once guarantees. A decentralized metropolitan architecture enhances reliability and minimizes latency while allowing data cleansing and enrichment for specific use cases. Validations against open-source tax-related datasets ensure quality. Windowing balances latency and cost. Queries rely on big-data-engine performance and seek result delivery under 10 seconds for alerting and under one minute for dashboard updating.

Cleansing minimizes errors, while enrichment offers new perspectives through derivation, expansion, and transformation. Provenance tracking captures origins and transformations throughout the entire analytics process. Quality-control checks assess response and latency delays based on Service-Level Agreements (SLAs). Validations incorporate external sources to foster confidence in original systems. Quality improvements depend on key property and control integration, particularly on schemas, and update database metadata.

Mathematical formulas:

1. Tax Compliance Rate

Measures the percentage of taxpayers complying with regulations.

$$TCR = \frac{N_c}{N_t} \times 100$$

Where:

- TCR= Tax Compliance Rate
- N_c= Number of compliant taxpayers
- N_t= Total taxpayers

2. Fraud Risk Score

Used in anomaly-based fraud analytics.

$$FRS = \sum_{i=1}^{n} w_i \, x_i$$

Where:

- FRS= Fraud Risk Score
- w_i= Weight of fraud indicator
- x_i= Fraud feature value

Examples of indicators:

- abnormal refund requests
- duplicate invoices
- suspicious transaction frequency

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3. Anomaly Detection using Z-Score
Useful for detecting abnormal taxpayer behavior.

$$Z = \frac{x - \mu}{\sigma}$$

$$x$$

$$\mu$$

$$\sigma$$

$$z = \frac{x - \mu}{\sigma} \approx 1.2$$

$$\Phi(z) \approx 88.5\%$$

Where:

- x= Observed transaction value
- μ= Mean transaction value
- σ= Standard deviation

If:

$$| Z |> 3$$

the transaction may be considered anomalous.

4. Stream Processing Latency
Measures real-time processing performance.

$$L = T_p - T_i$$

Where:

- L= Processing latency
- T_p= Processing completion time
- T_i= Data ingestion time

The paper targets:

- alerts under 10 seconds
- dashboard updates under 1 minute

5. Data Quality Accuracy
Measures correctness of ingested tax data.

$$DQA = \frac{R_v}{R_t} \times 100$$

Where:

- DQA= Data Quality Accuracy
- R_v= Valid records
- R_t= Total records

6. Precision for Fraud Detection Model
Evaluates fraud prediction quality.

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

Where:

- TP= True Positives
- FP= False Positives

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7. Recall for Fraud Detection
Measures ability to detect actual fraud cases.

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

Where:

- FN= False Negatives

8. F1-Score
Balances precision and recall.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

9. Data Throughput in Streaming Pipelines
Measures ingestion capacity.

$$Throughput = \frac{N}{T}$$

Where:

- N= Number of processed records
- T= Processing time

10. Cloud Resource Utilization
Used for elastic cloud scaling analysis.

$$RU = \frac{C_u}{C_t} \times 100$$

Where:

- RU= Resource Utilization
- C_u= Used compute resources
- C_t= Total allocated resources

11. Encryption Overhead
Evaluates security impact on processing.

$$EO = \frac{T_e - T_n}{T_n} \times 100$$

Where:

- EO= Encryption overhead
- T_e= Execution time with encryption
- T_n= Execution time without encryption

12. Differential Privacy Noise Injection
Used for privacy-preserving analytics.

$$M(x) = f(x) + Lap\left(\frac{\Delta f}{\epsilon}\right)$$

Where:

- $M(x)$= Private query result
- $f(x)$= Original query
- Δf= Sensitivity
- ϵ= Privacy budget

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13. K-Means Clustering Objective Function
Applicable for taxpayer anomaly clustering.

$$J = \sum_{i=1}^{k} \sum_{x_j \in C_i} || x_j - \mu_i ||^2$$

Where:

- J= Clustering loss
- C_i= Cluster i
- μ_i= Cluster centroid

14. SLA Availability Metric
Measures platform reliability.

$$Availability = \frac{Uptime}{Uptime + Downtime} \times 100$$

15. Fraud Probability using Logistic Regression
Common ML-based fraud prediction equation.

$$P(y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}}$$

Where:

- $P(y = 1)$= Probability of fraud
- β_i= Model coefficients
- x_i= Fraud-related features

16. Storage Cost Optimization
Used for hot/warm/cold storage analysis.

$$SC = \sum_{i=1}^{n} D_i \times C_i$$

Where:

- SC= Total storage cost
- D_i= Data volume in tier i
- C_i= Cost per storage tier

IV. DATA STORAGE AND PROCESSING PARADIGMS

In a cloud-native architecture, data can exist in hot, warm, or cold storage tiers, each optimizing infrastructure costs and performance to meet varied use case requirements. Three data models—structured (tabular), semi-structured (key-value, document), and unstructured (text, multimedia)—are employed, with the choice of model driven by the data representation best suited to specific analytical needs. Data in motion is typically processed in egress-load patterns to minimize cost, while data-at-rest consumption often aligns with egress-free availability. Each use case is met by the combination of storage tier, data model, and processing paradigm that best satisfies constraints of time, cost, and performance.

The choice of processing paradigm—streaming, micro-batching, or batch computing—also affects the allocation and balancing of compute resources. Although micro-batching can trigger higher latency compared with proper stream processing, it is frequently employed (e.g., for fraud detection) due to the built-in scalability of existing Apache-Spark-structured-streaming workloads and the ability to mitigate back-pressure challenges. Orchestration is commonly provided by Apache-Airflow. Use of a data catalog is crucial, serving as a data model repository for end-users and analytics pipelines, as well as centralizing the information necessary to enable metadata-based processing (e.g., that identifies radiography images requiring analysis). It is also fundamental to optimally managing metadata tags, including those indicating versioning, business-provenance, and data-sensitivity levels.

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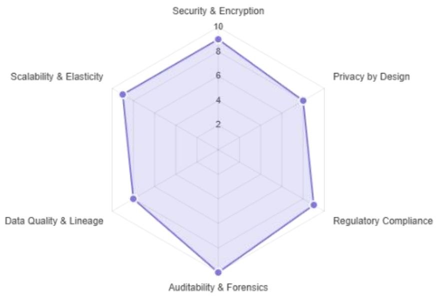
A schema registry is required for governance of representation and changes. Any change to the prevailing schema can impact a large number of dependent components (processing-and-consuming pipelines, consumed models) and thus must be captured, validated, and appropriately versioned.



Governance radar chart — a six-axis radar showing the architecture's relative emphasis across security, privacy, compliance, auditability, data quality/lineage, and scalability. Auditability and compliance score highest, reflecting the paper's focus on forensic traceability.

Table 2: Comparison of Processing Paradigms

Processing Paradigm	Latency	Scalability	Suitable Use Cases	Advantages
Batch Processing	High	Very High	Historical tax reporting	Cost-efficient
Micro-Batch Processing	Medium	High	Fraud analytics	Balanced performance
Stream Processing	Very Low	Medium-High	Real-time alerts	Instant insights

V. FRAUD DETECTION AND ANOMALY DETECTION IN TAX SYSTEMS

Detecting fraud is critical for any tax administration. Knowledge Discovery in Databases and Predictive Analysis have highlighted the main signals generally considered as indicative of fraud, such as purposeful discrepancy, distortion, manipulation, or concealment of data or a loop of operations conducted artificially across multiple entities. Various layers of knowledge discovery add additional dimensions to the search for tax fraud detection methods. Within tax systems, supervision and control often take the form of anomaly detection—identifying taxpayers whose behaviour does not match that of the majority. While vigilance committees may err on the side of caution, incorrectly flagging anomalous cases, an approach based on machine learning can automatically factor in behavioural patterns other than those of the majority; nevertheless, these models must relate the detected anomalies to a risk score to avoid trivial annoyance checks.

Anomalies can be detected through classification, regression, or clustering. Although the rules for K-means clustering are simple, confusion matrices and other evaluation criteria can indicate the model with the best clustering capabilities. However, such models should combine a degree of exploration with explanation in order to ensure a minimum noise-to-signal ratio. An annoyance risk rule should therefore combine predictive models with risk-signal methods and investigation results. Four types of fraud may need to be monitored: clear and explainable fraud signals (such as the use of similar bank accounts by many taxpayers in a possible carousel fraud); special cases that appear unusual because they do not follow the path of the majority, such as historical fraud cases; new fraud, such as transactions with entities that had recently become fraudulent; and abnormal symptom combinations, including those detected by modelling

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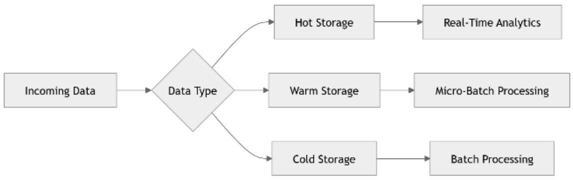
company internal data. Machine-learning-based fraud discovery should thus be included in a development cycle involving data engineers and fraud analysts and should incorporate data described in a #Data Dictionary.

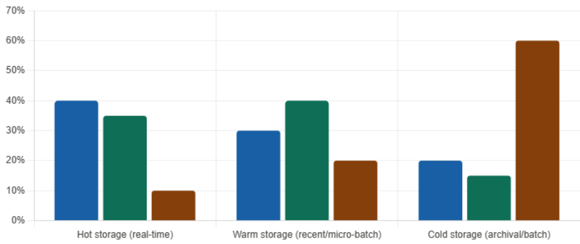


VI. GOVERNANCE, COMPLIANCE, AND AUDITABILITY IN THE CLOUD

Governance, Compliance, and Auditability in the Cloud: A formally defined governance framework aligned with existing rules, regulations, and other policies serves as the backbone of a well-functioning tax administration. Its components span provenance tracking for tax systems and underlying data, ensuring that institutions can demonstrate complete control over tax data and its use. Since reputation is vital for tax compliance, tax systems must include features that ensure auditability and forensic verification.

The whole data ecosystem is designed with absolute separation based on the principles of role-based (RBAC) and attribute-based (ABAC) access control models. The controls are enforced through dedicated policy enforcement points (PEPs) in data access, data loss prevention (DLP), and data sharing or publication. Data retention policies—defining legal holds for investigation and forensic purposes—also play a vital role in compliance reporting. Such legal hold declarations typically create extra constraints on data access. Compatibility with the data jurisdictions defined by the authorities provides the data locality required when data is either at rest or being processed. These provenance and auditability aspects serve as a gold standard for data traceability, enabling corresponding auto-formed audit reports.

As new types of fraud abuse emerge, fraud investigation signals can be constantly evolved according to available historical data on fraud events. Although there are many distinct areas in tax analytics and fraud detection, future research can focus on specific integrations towards an effective modular cloud-native architecture.



Storage tier vs. data model matrix — a grouped bar chart showing how structured, semi-structured, and unstructured data distributes across hot, warm, and cold storage tiers. Cold storage skews heavily unstructured (archival multimedia/text), while hot storage is dominated by structured tabular records.

Table 3: Data Types and Storage Tiers

Data Type	Example	Storage Tier	Purpose
Structured Data	Tax forms, invoices	Hot Storage	Real-time querying
Semi-Structured Data	JSON transaction logs	Warm Storage	Flexible analytics
Unstructured Data	Audit documents, multimedia	Cold Storage	Long-term archival

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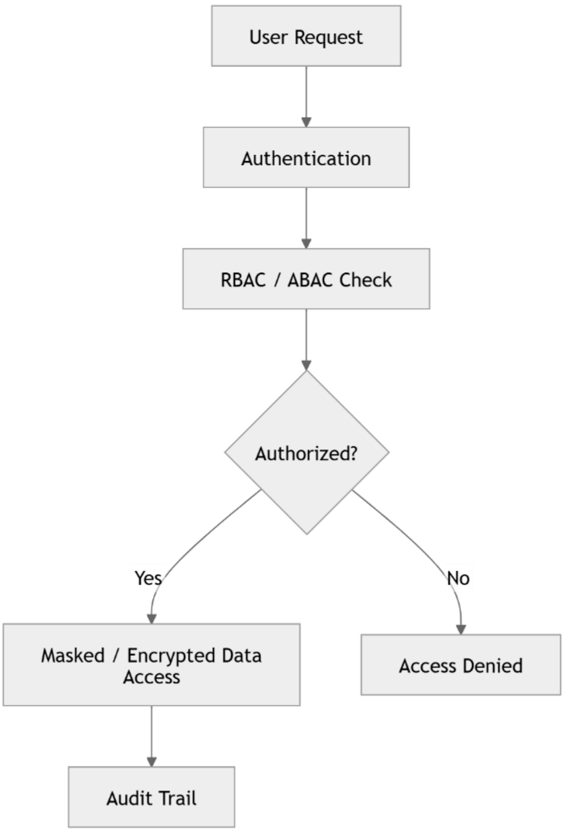
VII. SECURITY, PRIVACY, AND ACCESS CONTROL

Security, Privacy, and Access Control Identifying the threat model is crucial for effective security measures. Sensitive data is stored, making it a target for malicious actors. The architecture supports security features such as data encryption—both in transit and at rest using established industry encryption standards—and uses hardware security modules for key management. Fine-grained access in both external cloud applications and underlying data lakes is enforced, including periodic audits for suspicious activity. All systems incorporate zero-trust principles.

According to privacy-by-design principles, sensitive and financial information is masked to unauthorized and non-selected parties. In some use cases, end users may require representation of data as a valid data distribution. This may be achieved by using differential privacy techniques on query results, moving beyond data masking to more complex privacy issues and increasing disclosure risk management depending on system access requirements.

Students are tasked with creating a Cloud-Native Big Data Architecture for Real-Time Tax Analytics with the goals of tax fraud detection and prevention and tax erosion analysis. Existing architectures are referenced, with particular focus paid to security, privacy, compliance, and governance. Regular updates to the architecture are made, and future goals include establishing a dedicated tax fraud detection model.



VIII. CONCLUSION

For tax authorities, a flexible and scalable platform that supports real-time analytics, anomaly detection, and fraud detection with the cloud-native principles of elasticity, speed, modularity, and service orientation enables close monitoring of payment, refund, and credit requests. The reference architecture can be easily implemented and adapted with cloud services. For scalable analytics in a regulatory or compliance context, a well-designed and evidence-based fraud or anomaly detection model plays a crucial role. A statistical or ML prediction model predicts the risk or probability of the event, or detects an unexpected behavior. The model lifecycle with retraining, testing, and deployment stages guarantees continuous monitoring and maintenance.

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Such a cloud-native architecture platform can provide scalable tax analytics, tax fraud analysis, and regulatory compliance services in a connected society. The platform must include a governance model to ensure data quality, preserve data integrity, and comply with valid regulations and laws. It can be fine-tuned for real-time rule-based fraud and anomaly detection, and for timely and relevant categorization of tax fraud investigations using supervised ML and data mining.

Table 4: Fraud Detection Techniques in Tax Systems

Technique	Description	Use Case	Limitation
Classification	Categorizes fraudulent/non-fraudulent behavior	Tax evasion detection	Requires labeled data
Regression	Predicts fraud risk score	Revenue leakage estimation	Sensitive to outliers
Clustering	Groups similar anomalies	Suspicious transaction grouping	Difficult interpretation
Rule-Based Detection	Detects predefined fraud patterns	Carousel fraud	Limited adaptability
ML-Based Anomaly Detection	Learns unusual behaviors dynamically	Emerging fraud patterns	Higher computational cost

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