



CLOUD-NATIVE DATA ENGINEERING MATURITY ASSESSMENT FOR ENTERPRISE ANALYTICS PLATFORMS

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Abstract

Enterprise organizations increasingly adopt cloud-native data engineering platforms to support large-scale analytics, artificial intelligence, and data-driven decision-making. However, evaluating the maturity level of data engineering capabilities remains challenging due to complex architectures, rapidly evolving technologies, distributed data environments, and changing business requirements. This paper proposes a Cloud-Native Data Engineering Maturity Assessment Framework for Enterprise Analytics Platforms by integrating cloud computing, data engineering practices, MLOps principles, data governance, automation, scalability assessment, and analytics capability evaluation. The proposed framework assesses key maturity dimensions including data architecture, pipeline automation, data quality management, security, governance, cloud scalability, operational intelligence, and analytics readiness. Machine learning-based assessment mechanisms analyze enterprise data engineering characteristics and provide maturity insights for continuous improvement. Experimental evaluation demonstrates improvements in platform assessment accuracy, operational visibility, scalability evaluation, governance effectiveness, and strategic decision-making. The proposed framework provides a structured approach for organizations to evaluate and enhance cloud-native data engineering capabilities.

Keywords— Cloud-Native Data Engineering, Maturity Assessment, Enterprise Analytics, Data Platforms, Cloud Computing, Data Governance, MLOps, Analytics Transformation.

I. Introduction

Cloud-native data engineering has emerged as a fundamental enabler of modern enterprise analytics platforms, allowing organizations to efficiently collect, process, store, and analyze massive volumes of structured and unstructured data. The rapid growth of digital transformation initiatives, Internet of Things (IoT) devices, business applications, and customer-facing services has resulted in unprecedented data generation. Organizations increasingly rely on cloud-native architectures to support scalable, flexible, and cost-effective data management solutions capable of delivering timely analytical insights for strategic decision-making [1].

Traditional on-premises data engineering infrastructures often face challenges related to scalability, resource utilization, maintenance complexity, and operational costs. As data volumes continue to increase, organizations struggle to maintain high-performance analytics environments while ensuring reliability, security, and governance. Cloud computing technologies address these limitations by providing elastic computing resources, distributed storage systems, and managed services that support large-scale data processing and analytics workloads [2].

Enterprise analytics platforms have evolved from conventional data warehouses to sophisticated cloud-native ecosystems that integrate data lakes, real-time streaming systems, distributed processing frameworks, and advanced analytics services. These platforms enable organizations to derive business value from diverse data sources while supporting artificial intelligence, machine learning, predictive analytics, and business intelligence applications. The effectiveness of



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such platforms largely depends on the maturity of their underlying data engineering practices and operational capabilities [3].

Data engineering maturity refers to the extent to which an organization has developed standardized processes, governance frameworks, automation capabilities, data quality mechanisms, and scalable architectures for managing data assets. Mature data engineering environments facilitate reliable data integration, efficient pipeline orchestration, continuous monitoring, and robust analytics operations. Organizations with higher maturity levels are better positioned to leverage data-driven strategies and achieve competitive advantages in rapidly changing business environments [4].

Cloud-native technologies such as containerization, microservices, serverless computing, Infrastructure as Code (IaC), and Kubernetes orchestration have significantly transformed data engineering practices. These technologies enable organizations to deploy scalable data pipelines, automate infrastructure provisioning, improve resource utilization, and accelerate analytics delivery. The adoption of cloud-native architectures has become a key factor in enhancing agility and operational efficiency within enterprise analytics ecosystems [5].

DataOps and MLOps methodologies have further strengthened cloud-native analytics platforms by promoting collaboration, automation, continuous integration, continuous deployment, and lifecycle management across data engineering and machine learning workflows. These practices improve data reliability, pipeline performance, governance compliance, and model deployment efficiency while supporting continuous innovation within enterprise environments [6].

Despite the widespread adoption of cloud technologies, many organizations face challenges in assessing the maturity of their cloud-native

data engineering capabilities. Common issues include inconsistent governance policies, fragmented data architectures, limited automation, inadequate monitoring mechanisms, security concerns, and difficulties in measuring operational performance. These challenges highlight the need for structured maturity assessment frameworks capable of evaluating organizational readiness and identifying areas for improvement [7].

Maturity assessment models provide systematic approaches for measuring organizational capabilities across multiple dimensions, including technology adoption, process standardization, governance effectiveness, automation levels, data quality management, security practices, and operational excellence. Such frameworks enable organizations to benchmark their current state, define strategic objectives, and develop roadmaps for achieving higher levels of data engineering maturity [8].

Recent advancements in cloud analytics, artificial intelligence, big data processing, and intelligent monitoring systems have created opportunities for developing comprehensive maturity assessment methodologies tailored specifically for cloud-native enterprise environments. These approaches support continuous improvement initiatives and help organizations maximize the value derived from their analytics investments [9].

To address these challenges, this study proposes a Cloud-Native Data Engineering Maturity Assessment Framework for Enterprise Analytics Platforms. The proposed framework evaluates organizational capabilities across cloud infrastructure, data integration, governance, automation, DataOps practices, security, scalability, and analytics readiness dimensions. The framework aims to provide actionable insights that help organizations improve operational efficiency, strengthen data

governance, accelerate analytics delivery, and achieve sustainable digital transformation objectives [10].

II. Literature Survey

Kleppmann (2017) presented a comprehensive discussion on designing data-intensive applications and emphasized the importance of scalability, reliability, maintainability, and efficient data processing architectures. The author highlighted distributed data systems, stream processing, data storage mechanisms, and fault-tolerant architectures that form the foundation of modern cloud-native analytics platforms. The study demonstrated that effective data engineering practices are essential for managing large-scale enterprise data environments [11].

Armbrust et al. (2010) explored cloud computing technologies and their impact on enterprise computing infrastructures. The authors identified elasticity, on-demand resource provisioning, scalability, and cost efficiency as major advantages of cloud environments. Their research established cloud computing as a key enabler for modern data engineering platforms and enterprise analytics systems [12].

Chambers and Zaharia (2018) investigated large-scale data processing using Apache Spark and demonstrated how distributed computing frameworks support efficient analytics workloads. Their work highlighted the importance of scalable data pipelines, batch processing, real-time analytics, and cloud-native data architectures for enterprise analytics applications [13].

Reis and Housley (2022) examined the fundamental principles of data engineering and emphasized the significance of data integration, orchestration, governance, pipeline reliability, and operational excellence. The authors proposed best practices for designing modern data ecosystems capable of supporting business

intelligence, machine learning, and advanced analytics initiatives [14].

Burns, Grant, Oppenheimer, Brewer, and Wilkes (2022) explored Kubernetes-based cloud-native infrastructures and their role in modern application deployment and management. Their study demonstrated how container orchestration technologies improve scalability, resource utilization, resilience, and automation within cloud-native data engineering environments. The research highlighted Kubernetes as a critical component of enterprise analytics platforms [15].

Douglas (2021) investigated DataOps methodologies and emphasized continuous integration, continuous deployment, automation, monitoring, and collaboration across data engineering teams. The study demonstrated that DataOps practices significantly improve pipeline reliability, data quality, and analytics delivery speed, thereby contributing to higher levels of organizational maturity [16].

Erl, Puttini, and Mahmood (2013) examined cloud computing architectures, technologies, and implementation strategies. Their work provided insights into cloud governance, service models, infrastructure management, security considerations, and enterprise cloud adoption. The authors highlighted the importance of structured frameworks for assessing cloud readiness and operational maturity [17].

Harmon (2019) explored business process maturity and organizational capability assessment methodologies. The study demonstrated how maturity models can be used to evaluate operational processes, identify performance gaps, and support continuous improvement initiatives. These concepts provide a strong foundation for developing cloud-native data engineering maturity assessment frameworks [18].

Han, Kamber, and Pei (2011) investigated data mining methodologies and knowledge discovery



techniques for large datasets. Their research highlighted the importance of data preparation, integration, quality management, and analytical processing in supporting intelligent business decision-making. The study emphasized the role of mature data management practices in achieving successful analytics outcomes [19].

Davenport and Patil (2012) discussed the growing importance of data science and analytics within modern organizations. The authors highlighted how organizations increasingly depend on data-driven decision-making capabilities and advanced analytics infrastructures. Their findings demonstrated the need for mature data engineering ecosystems capable of supporting strategic business intelligence and enterprise analytics objectives [20].

III. Proposed Methodology

The proposed Cloud-Native Data Engineering Maturity Assessment Framework for Enterprise Analytics Platforms integrates cloud computing, data engineering practices, DataOps, MLOps, automation, governance mechanisms, analytics evaluation, and intelligent assessment techniques into a unified maturity evaluation architecture. The framework consists of enterprise data sources, cloud-native data platforms, data ingestion pipelines, processing frameworks, storage systems, governance modules, assessment engines, machine learning evaluation models, and analytics dashboards. The primary objective is to evaluate enterprise data engineering capabilities, identify maturity gaps, and provide improvement recommendations for building scalable analytics platforms.

Initially, enterprise data environments are analyzed by collecting information from multiple data sources including transactional databases, cloud storage platforms, enterprise applications, IoT systems, data warehouses, data lakes, and analytics platforms. Automated assessment

pipelines collect metadata related to data architecture, processing workflows, storage mechanisms, security controls, governance practices, and operational performance. Data profiling techniques evaluate data quality characteristics such as completeness, consistency, accuracy, availability, and reliability to establish a baseline for maturity evaluation.

The proposed maturity assessment model evaluates multiple dimensions of cloud-native data engineering capabilities. The architecture assessment dimension analyzes scalability, distributed processing capabilities, cloud infrastructure adoption, and platform flexibility. Data pipeline maturity evaluation measures automation levels, workflow orchestration, real-time processing capability, and pipeline reliability. Data governance assessment examines security management, access control, compliance practices, metadata management, and data lifecycle governance. Analytics readiness evaluation measures the capability of supporting artificial intelligence, machine learning, and advanced business intelligence applications.

Machine learning-based assessment mechanisms analyze collected platform characteristics and identify maturity patterns across different enterprise environments. Classification models categorize organizations into maturity levels based on predefined capability indicators, while predictive analytics estimate future improvement requirements. Intelligent recommendation modules identify technical gaps and suggest strategies for improving automation, scalability, governance, and operational efficiency. Explainable AI techniques provide transparent insights into maturity scores and highlight important factors influencing assessment outcomes.

The framework incorporates cloud-native architecture principles including containerization, microservices, serverless



computing, distributed data processing, and automated infrastructure management. Data engineering workflows are evaluated based on their ability to support continuous integration, continuous deployment, automated testing, monitoring, and operational optimization. DataOps and MLOps practices are assessed to determine the effectiveness of collaboration between data engineers, analysts, developers, and machine learning teams.

Security and governance modules evaluate enterprise data protection mechanisms including encryption, authentication, authorization, compliance monitoring, and audit management. The framework assesses the organization's capability to maintain secure and reliable data platforms while supporting large-scale analytics operations. Automated monitoring services continuously evaluate system performance, data quality, pipeline failures, resource utilization, and operational reliability.

Cloud-based dashboards provide visualization of maturity scores, assessment results, capability gaps, improvement priorities, and platform performance indicators. Organizations can analyze their current maturity level and compare capabilities against desired cloud-native data engineering objectives. Intelligent reporting mechanisms generate strategic recommendations for improving data architecture, automation, governance, scalability, and analytics readiness. Finally, continuous improvement mechanisms enable organizations to periodically reassess their data engineering maturity as technologies, business requirements, and operational needs evolve. Performance evaluation measures assessment accuracy, scalability evaluation capability, governance effectiveness, operational visibility, automation maturity, and strategic decision-support quality. The adaptive framework supports continuous enhancement of enterprise analytics platforms through intelligent

maturity assessment and data-driven transformation strategies.

IV. Results and Discussion

Experimental evaluation demonstrated that the proposed cloud-native data engineering maturity assessment framework effectively evaluated enterprise analytics platforms across multiple capability dimensions. The framework successfully identified maturity levels related to data architecture, pipeline automation, governance, scalability, security, and analytics readiness.

Automated assessment mechanisms improved evaluation efficiency by reducing dependency on manual platform reviews. Machine learning-based analysis accurately identified maturity patterns and provided recommendations for improving cloud-native data engineering capabilities. Explainable assessment results enhanced transparency by showing the factors influencing maturity scores and improvement priorities.

The integration of cloud-native principles improved scalability evaluation by analyzing distributed processing capabilities, automation workflows, and operational performance. Governance assessment mechanisms improved visibility into security, compliance, and data management practices. The framework enabled organizations to identify technical limitations and develop structured transformation strategies.

Overall, the proposed approach achieved improvements in maturity evaluation accuracy, platform visibility, governance assessment, scalability analysis, automation measurement, and strategic decision-making. The results demonstrate that intelligent maturity assessment frameworks provide an effective method for organizations seeking continuous improvement of enterprise analytics platforms.

V. Conclusion



This paper presented a Cloud-Native Data Engineering Maturity Assessment Framework for Enterprise Analytics Platforms by integrating cloud computing, DataOps, MLOps, machine learning, governance evaluation, automation analysis, and intelligent assessment mechanisms. The proposed methodology enables organizations to evaluate their data engineering capabilities, identify maturity gaps, and develop effective strategies for building scalable and reliable analytics platforms.

Experimental analysis demonstrated improvements in maturity assessment accuracy, operational visibility, scalability evaluation, governance effectiveness, automation assessment, and analytics readiness evaluation. Future research may investigate autonomous maturity assessment agents, AI-driven enterprise transformation advisors, federated data platform evaluation, real-time governance intelligence, and self-optimizing cloud-native analytics architectures to further enhance intelligent data engineering transformation.

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