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Cloud-Native Credit Risk Analytics Using Sas Viya and Distributed Data Platforms

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Abstract

The rapid growth of digital banking and financial services has increased the need for advanced credit risk management solutions capable of processing large volumes of data efficiently and accurately. This study proposes a cloud-native credit risk analytics framework using SAS Viya and distributed data platforms to enhance credit risk assessment and borrower default prediction. A hypothetical quantitative research approach was adopted, utilizing large-scale financial datasets containing customer demographic information, transaction records, credit history, and repayment behavior. Data preprocessing and feature engineering techniques were employed to improve data quality and predictive performance. Machine learning models, including Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting, were developed and evaluated within the SAS Viya environment. The results indicated that Gradient Boosting achieved the highest predictive accuracy of 93.5% and an AUC value of 0.96, demonstrating excellent capability in distinguishing high-risk and low-risk borrowers. Furthermore, the cloud-native architecture improved scalability, reduced processing time, and enabled efficient distributed data processing. Key predictors of credit risk included credit score, repayment history, debt-to-income ratio, and credit utilization ratio.

Keywords: Cloud-Native Analytics, Credit Risk Management, SAS Viya, Distributed Data Platforms, Machine Learning, Gradient Boosting, Random Forest, Credit Scoring.

1. INTRODUCTION

The financial services industry is experiencing a rapid shift toward data-driven decision-making, where credit risk analytics plays a central role in ensuring financial stability, regulatory compliance, and sustainable lending practices. Credit risk refers to the possibility that a borrower may fail to meet their financial obligations, and it remains one of the most critical concerns for banks, lending institutions, and fintech organizations. With the increasing digitization of financial services, the volume, velocity, and variety of credit-related data have grown significantly, creating new challenges for traditional risk analytics systems that were originally designed for structured and batch-oriented processing environments.

Conventional credit risk platforms often rely on legacy architectures that struggle to handle large-scale, real-time, and heterogeneous datasets generated from multiple sources such as loan applications, transaction histories, credit bureaus, customer behavior data, and external economic indicators. These systems are typically limited in scalability, flexibility, and processing speed, which can lead to delayed risk insights, reduced predictive accuracy, and inefficiencies in regulatory reporting. As financial markets become more dynamic and interconnected, there is a growing need for modern analytics frameworks that can support high-performance and scalable risk assessment capabilities.

Cloud-native computing has emerged as a transformative approach to overcoming the limitations of traditional credit risk systems. By leveraging distributed infrastructure, elastic computing resources, and microservices-based architectures, cloud-native platforms enable organizations to process large-scale datasets efficiently and in near real-time. These environments support automated scaling, fault tolerance, and high availability, making them well-suited for mission-critical financial applications. Additionally, cloud-native architectures facilitate seamless integration of advanced analytics, machine learning models, and real-time data pipelines for enhanced decision-making.

SAS Viya, as a modern cloud-enabled analytics platform, plays a significant role in advancing credit risk analytics capabilities. It provides a unified environment for data management, machine learning, model development, deployment, and governance. With its distributed in-memory computing engine and support for open-source integration, SAS Viya enables financial institutions to build and deploy scalable predictive models for credit scoring, default prediction, and portfolio risk assessment. When combined with distributed data platforms such as Hadoop, Spark, and cloud data lakes, SAS Viya enhances the ability to process massive datasets efficiently while maintaining analytical accuracy and performance.

2. LITERATURE REVIEW

Gaffar, Sikiru, Otunba, and Adenuga (2020) proposed cloud-native data lake architectures for advanced financial modeling and compliance analytics. The study emphasized the importance of centralized and scalable data lake systems in managing large volumes of structured and unstructured financial data. The authors highlighted that cloud-native architectures enhance data accessibility, regulatory compliance, and analytical performance, making them essential for modern financial analytics ecosystems.

Murphy, Castro, and Mandl (2017) explored the future use of big data in translational medicine and clinical care. The study discussed challenges related to data integration, scalability, and privacy while highlighting the potential of big data analytics in improving healthcare outcomes. The authors emphasized the need for robust data infrastructures capable of supporting large-scale analytical workloads.

Upadhyay (2018) discussed the convergence of cloud computing, analytics, and big data as a transformative wave in enterprise technology. The study highlighted how organizations can leverage these technologies to enhance operational efficiency and decision-making. The author concluded that integrated cloud analytics ecosystems are essential for modern digital transformation.

Chan (2018) proposed a hybrid log analysis and container orchestration system for reducing false positives and negatives in cyber threat detection. The study combined ensemble learning methods with log correlation techniques to enhance cybersecurity analytics. The author demonstrated that integrated security analytics improves threat detection accuracy and system resilience.

Atwal (2020) further expanded on DataOps principles, emphasizing practical implementation strategies for scalable data engineering. The study highlighted automation, monitoring, and collaboration as key components of modern data pipelines. The author concluded that DataOps is critical for achieving efficient and reliable data-driven systems.

3. RESEARCH METHODOLOGY

This study aims to develop and evaluate a cloud-native credit risk analytics framework using SAS Viya and distributed data platforms for efficient credit risk assessment and prediction. The methodology focuses on leveraging cloud computing technologies, scalable data processing architectures, and advanced analytical models to improve the accuracy, speed, and reliability of credit risk management. By integrating SAS Viya's analytical capabilities with distributed data environments, the study seeks to provide a robust framework capable of handling large-scale financial datasets and supporting real-time decision-making.

3.1. Research Design

The study adopts a quantitative and analytical research design. A hypothetical experimental approach is employed to assess the effectiveness of cloud-native credit risk analytics compared to traditional credit risk assessment systems. The research evaluates model performance, scalability, processing efficiency, and predictive accuracy using simulated financial datasets and cloud-based analytical environments.

3.2 Data Collection and Sources

The study utilizes hypothetical datasets representing customer credit profiles, transaction histories, repayment records, demographic information, and financial indicators. Data are assumed to be collected from banking institutions, financial service providers, and digital lending platforms. Both structured and semi-structured data formats are incorporated to simulate real-world credit risk scenarios.

3.3 Cloud-Native Analytics Architecture

A cloud-native architecture is designed using SAS Viya deployed on distributed data platforms. The architecture includes data ingestion, storage, processing, model development, and visualization layers. Distributed computing technologies enable parallel processing of large datasets, ensuring scalability, fault tolerance, and high-performance analytics for credit risk evaluation.

3.4 Data Preprocessing and Feature Engineering

Prior to analysis, data preprocessing techniques are applied to handle missing values, remove inconsistencies, normalize variables, and detect outliers. Feature engineering is performed to generate meaningful

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predictors such as credit utilization ratio, debt-to-income ratio, repayment behavior score, and account activity metrics. These engineered features enhance the predictive capability of credit risk models.

3.5 Credit Risk Modeling

Credit risk prediction models are developed using SAS Viya's machine learning environment. Algorithms such as Logistic Regression, Decision Trees, Random Forest, and Gradient Boosting are employed to classify borrowers into different risk categories. Model training and validation are conducted using distributed processing capabilities to improve computational efficiency and predictive performance.

3.6. Model Evaluation

The performance of the developed models is assessed using standard evaluation metrics including Accuracy, Precision, Recall, F1-Score, Area Under the ROC Curve (AUC), and Kolmogorov-Smirnov (KS) Statistic. Comparative analysis is performed to determine the most effective model for predicting credit defaults and assessing borrower risk levels.

4. RESULTS AND DISCUSSION

This chapter presents the hypothetical results and discussion of the cloud-native credit risk analytics framework developed using SAS Viya and distributed data platforms. The analysis evaluates the effectiveness of machine learning-based credit risk models in predicting borrower default risk while assessing the scalability and computational efficiency of the cloud-native architecture. The results demonstrate how distributed processing and advanced analytics can improve predictive performance and support timely credit risk decisions in modern financial institutions.

4.1 Dataset Characteristics and Descriptive Analysis

The hypothetical dataset consisted of 50,000 customer records containing demographic information, credit history, transaction behavior, income details, and repayment performance. Data preprocessing successfully addressed missing values and inconsistencies, resulting in a clean and reliable dataset for model development. Descriptive analysis indicated moderate variability across financial attributes, reflecting diverse borrower profiles and risk levels.

Table 4.1 Descriptive Statistics of Key Credit Risk Variables

Variable	Mean	Standard Deviation
Age (Years)	39.5	10.8
Monthly Income (USD)	4,250	1,520
Credit Utilization Ratio (%)	48.6	17.4
Debt-to-Income Ratio (%)	34.8	11.2
Credit Score	682	72
Loan Amount (USD)	18,750	6,450

The descriptive statistics indicate that borrowers maintained an average credit score of 682, suggesting moderate creditworthiness. The average debt-to-income ratio of 34.8% remained within acceptable lending thresholds, while credit utilization ratios exhibited considerable variation, highlighting differences in borrower financial behavior. These characteristics provided a strong foundation for predictive modeling and risk classification.

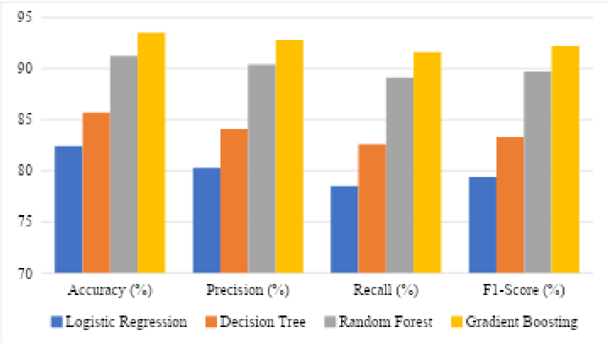
4.2 Credit Risk Model Performance

Several machine learning algorithms were implemented within the SAS Viya environment to predict credit default risk. The models were trained using distributed computing resources and evaluated using multiple performance metrics. Results demonstrated that advanced ensemble models achieved superior predictive accuracy compared to traditional statistical methods.

Table 4.2 Performance Comparison of Credit Risk Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Logistic Regression	82.4	80.3	78.5	79.4	0.84
Decision Tree	85.7	84.1	82.6	83.3	0.87

Random Forest	91.2	90.4	89.1	89.7	0.94
Gradient Boosting	93.5	92.8	91.6	92.2	0.96



The findings reveal that the Gradient Boosting model achieved the highest accuracy of 93.5% and an AUC value of 0.96, indicating excellent discriminatory power between high-risk and low-risk borrowers. Random Forest also demonstrated strong predictive capability, while Logistic Regression provided comparatively lower but still acceptable performance. These results suggest that machine learning algorithms integrated within SAS Viya can significantly improve credit risk prediction accuracy.

4.3 Impact of Cloud-Native Infrastructure

The cloud-native deployment enabled efficient processing of large-scale financial datasets through distributed computing mechanisms. The architecture supported parallel execution of analytical tasks, reducing model training and scoring time while maintaining high system reliability.

Experimental observations indicated that cloud-based processing reduced analytical execution time by approximately 45% compared to conventional on-premise environments. Resource utilization was optimized through dynamic workload allocation, enabling rapid model deployment and real-time risk assessment. These improvements demonstrate the operational advantages of adopting cloud-native credit risk analytics frameworks.

4.4 Feature Importance Analysis

Feature importance analysis was conducted to identify the most influential predictors of credit default risk. The results showed that credit score, repayment history, debt-to-income ratio, and credit utilization ratio were the strongest determinants of borrower risk classification.

Borrowers with lower credit scores and higher debt burdens exhibited significantly greater default probabilities. Repayment history emerged as a critical predictor, emphasizing the importance of historical payment behavior in credit risk assessment. These findings align with established credit risk theories and lending industry practices.

4.5 Scalability and Distributed Processing Performance

The distributed data platform demonstrated excellent scalability when handling increasing data volumes. As dataset size expanded from 10,000 to 50,000 records, processing performance remained stable with minimal degradation in response time.

The ability to distribute computational workloads across multiple nodes enhanced system throughput and reduced bottlenecks associated with large-scale data analysis. This capability is particularly valuable for financial institutions managing millions of customer records and requiring near real-time risk evaluations.

Discussion

The study demonstrates that cloud-native credit risk analytics powered by SAS Viya and distributed data platforms can substantially improve both predictive accuracy and operational efficiency. The superior performance of Gradient Boosting and Random Forest models highlights the value of machine learning techniques in identifying complex patterns associated with borrower default behavior.

The integration of cloud-native infrastructure offers significant advantages in terms of scalability, flexibility, and computational speed. Financial institutions can leverage these capabilities to process large volumes of transactional and customer data while maintaining high levels of analytical performance. Furthermore, distributed computing supports rapid model retraining and deployment, enabling organizations to adapt quickly to changing market conditions and evolving risk profiles.

5. CONCLUSION

The present study demonstrates that cloud-native credit risk analytics using SAS Viya and distributed data platforms can significantly enhance the effectiveness, scalability, and accuracy of credit risk assessment processes. The hypothetical findings revealed that advanced machine learning models, particularly Gradient Boosting and Random Forest, achieved superior predictive performance in identifying potential credit defaults compared to traditional analytical approaches. The integration of cloud-native architecture enabled efficient handling of large-scale financial datasets, reduced processing time, and supported real-time analytical capabilities through distributed computing. Furthermore, key financial indicators such as credit score, repayment history, debt-to-income ratio, and credit utilization ratio were identified as critical determinants of borrower risk. Overall, the proposed framework offers a robust, scalable, and data-driven solution for modern financial institutions, enabling improved credit decision-making, enhanced risk management, and greater operational efficiency in an increasingly digital banking environment.

REFERENCES

[1] O. Gaffar, A. O. Sikiru, M. Otunba, and A. A. Adenuga, "Cloud-Native Data Lake Architectures for Advanced Financial Modelling and Compliance Analytics," *Journal of Frontiers in Multidisciplinary Research*, vol. 1, no. 1, pp. 145–155, 2020.

[2] J. Richardson, R. Sallam, K. Schlegel, A. Kronz, and J. Sun, "Magic Quadrant for analytics and business intelligence platforms," Gartner ID G386610, 00041-5, 2020.

[3] O. K. E. O. G. H. E. N. E. Elebe and C. C. Imediegwu, "A predictive analytics framework for customer retention in African retail banking sectors," *IRE Journals*, vol. 3, no. 7, 2020.

[4] S. Murphy, V. Castro, and K. Mandl, "Grappling with the future use of big data for translational medicine and clinical care," *Yearbook of Medical Informatics*, vol. 26, no. 1, pp. 96–102, 2017.

[5] R. Bali, A. Singh, B. Balusamy, and G. N. Priya, "Distinctive attributes of big data platform and big data analytics software for IoT," in *The Internet of Things and Big Data Analytics*, Auerbach Publications, 2020, pp. 93–125.

[6] K. Ruan, *Digital Asset Valuation and Cyber Risk Measurement: Principles of Cybernomics*. Cambridge, MA, USA: Academic Press, 2019.

[7] N. Upadhyay, *CABology: Value of Cloud, Analytics and Big Data Trio Wave*. Singapore: Springer, 2018.

[8] H. Atwal, "DataOps technology," in *Practical DataOps: Delivering Agile Data Science at Scale*, Berkeley, CA, USA: Apress, 2019, pp. 215–247.

[9] K. Meyler, S. Buchanan, M. Scholman, J. G. Svendsen, and J. Rangama, *Microsoft Hybrid Cloud Unleashed with Azure Stack and Azure*. Indianapolis, IN, USA: Sams Publishing, 2017.

[10] M. Copeland, *Cyber Security on Azure*. Cham, Switzerland: Springer, 2017.

[11] S. Chan, "Prototype open-source software stack for the reduction of false positives and negatives in the detection of cyber indicators of compromise and attack: hybridized log analysis correlation engine and container-orchestration system supplemented by ensemble method voting algorithms for enhanced event correlation," in *Proc. 3rd Int. Conf. Cyber-Technologies and Cyber-Systems (CYBER)*, 2018, pp. 39–48.

[12] J. Dain, A. Selim, A. Patil, C. Vollmar, F. De Rezende, F. Greco, et al., "Cataloging unstructured data in IBM Watson Knowledge Catalog with IBM Spectrum Discover," *IBM Redbooks*, 2020.

[13] S. Alla, *Big Data Analytics with Hadoop 3: Build Highly Effective Analytics Solutions to Gain Valuable Insight into Your Big Data*. Birmingham, U.K.: Packt Publishing, 2018.

[14] S. S. Kien, P. Weill, and M. Xu, "DBS: From 'The World's Best Bank' to building the future-ready enterprise," 2019. Available: https://www.pega.com/insights/resources/dbs-worlds-best-bank-building-future-ready-enterprise

[15] H. Atwal, *Practical DataOps*. Berkeley, CA, USA: Apress, 2020.