Adopting ML Techniques to Manage IT Systems:

AIOps Case Study on the Royal Bank of Canada

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February 16, 2024

Executive Summary

RBC addresses credit risk and operational challenges by leveraging text mining and advanced analytics. The transition to techniques like sentiment analysis, favored for its agility in assessing borrower sentiment, involves tools like NLTK, TextBlob, and IBM Watson. Additionally, source code quality is vital for RBC's digital services, with performance metrics including cyclomatic complexity, time complexity, and execution time ensuring software performance. The integration of AIOps for IT operations automation further enhances system efficiency and reliability. This holistic approach underscores RBC's commitment to using technology for managing risks and improving operational effectiveness in a dynamic economic landscape, fostering a resilient and responsive banking environment amidst evolving credit risks.

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Introduction

This report explores the critical business challenges faced by Royal Bank of Canada (RBC) amid the COVID-19 pandemic's economic repercussions, focusing on the heightened concerns around credit risk. Credit risk, the likelihood of a borrower defaulting on loan obligations, has become a significant issue for RBC, with a notable increase in gross impaired loans signaling potential financial instability. This situation not only affects RBC's financial health through possible losses and increased loan provisions but also poses risks of reputational damage and regulatory scrutiny.

As a leading commercial lender, RBC's response to these challenges is critical for maintaining financial stability. This report introduces text mining as a transformative solution that leverages unstructured text, converting it into structured data for comprehensive risk analysis. This approach includes sentiment analysis and Word2Vec methodologies that can significantly enhance RBC's ability to assess and manage credit risk efficiently by uncovering insights from borrower sentiment to economic conditions affecting creditworthiness. However, each method comes with its challenges, including data privacy concerns, the need for continuous model retraining, and potential inaccuracies in sentiment interpretation.

In addition to addressing credit risk analysis, the document underscores the importance of code quality in RBC's digital client experience, particularly through its online banking application. It discusses the use of metrics like cyclomatic complexity, time complexity and execution time as indicators of code performance, which are crucial for ensuring client satisfaction and operational efficiency. The document also highlights the role of AIOps in enhancing IT operations, offering a comprehensive view of how RBC can leverage technology to navigate the complexities of the current economic environment and beyond.

This introduction sets the stage for a detailed examination of how RBC can employ advanced techniques and technology solutions to address the multi-dimensional challenges of credit risk management and operational efficiency in a post-pandemic economic landscape.

Text Mining

RBC is facing a critical business problem of heightened credit risk concerns in the current economic landscape marked by the impacts of COVID-19. Credit risk refers to the likelihood of financial loss due to a borrower's inability to repay a loan. It includes individual and commercial credit risk regarding the default by individuals and corporate entities. In 2023, RBC's gross impaired loans increased by 68% from the year-earlier period, indicating a higher level of loans at risk of default (Shecter, 2023). This concern suggests an impact on RBC through financial losses, higher loan loss provisions, reputational harm, and increased regulatory scrutiny. A recent study also highlights that tighter financial conditions are impacting Vancouver's commercial real estate developers, and the uncertain office space demand creates potential credit risks for lenders in this sector (Korstrom,2023). As a leading commercial lender in Canada, effective risk management in RBC is critical to mitigate potential losses and ensure financial stability. Typically, traditional credit risk analysis involves manual reviews of documentation. However, with the vast amount of unstructured data for credit risk analysis, traditional methods may not capture all relevant information. Text mining offers a transformative solution by converting unstructured text into structured data, allowing for the

identification of significant patterns and insights (IBM Text, n.d.). Through text mining, RBC can efficiently analyze large volumes of unstructured data and uncover valuable insights on risk factors such as borrower sentiment. This method can enhance the bank's lending decision, improve approval accuracy and minimize the need for manual analysis, leading to cost savings and operational expenses.

One solution to credit risk assessment is sentiment analysis, which emerges as a useful solution by identifying positive or negative sentiments related to borrowers, specific industries, or prevailing economic conditions. This analytical method enhances the decision-making process by providing insights not readily apparent in traditional financial data. According to Kremer et al., using traditional credit-rating models, banks face limitations such as their reliance on outdated financial reports and simplistic qualitative assessments (2013). Sentiment analysis on textual data such as credit reports and social media posts can provide valuable insights about borrowers that can help overcome these challenges. Key to this process is identifying features that are crucial for accurate sentiment classification and important textual data insights such as:

1. Sentiment-Laden Language: Terms and expressions that directly or indirectly convey sentiments or opinions. This could include adjectives, verbs, nouns, and idioms that express a positive or negative viewpoint, such as "excellent" (positive) or "poor" (negative).
2. Negation: Words like "not," "never," and "no" that can alter the sentiment.
3. Financial Risk Indicators: Text indicative of financial conditions (e.g., bankruptcy filings)
4. Topics: Topics about credit risk factors, such as economic indicators (e.g., inflation).

Sentiment analysis offers considerable advantages in credit risk assessment by providing comprehensive qualitative insights. It delves deep into customer perceptions and market sentiment, allowing RBC to uncover subtleties that are not captured by traditional quantitative metrics, thereby offering a more nuanced view of a borrower’s overall financial health. Furthermore, the tool’s capacity for real-time monitoring through social media and news outlets enables RBC to actively measure public sentiment toward corporate borrowers, quickly pinpointing potential risks as they surface in the public view. This immediate feedback is critical for responding quickly to shifts in a borrower's credit standing. Additionally, sentiment analysis streamlines the workload by handling the automated analysis of large data volumes, substantially decreasing the need for manual data processing.

While using sentiment analysis in credit risk assessment is beneficial, it also comes with its disadvantages and challenges. A primary concern is the accuracy of interpretation; natural language processing tools may misinterpret the nuances of human emotions and language, such as sarcasm, which results in inaccurate interpretation (Determ, 2024). For instance, a customer sarcastically saying, “Yeah, excellent. It took three weeks for my food delivery to arrive,” could be incorrectly classified as a positive sentiment. Furthermore, language is evolving and requires continuous updates and retraining of sentiment analysis models to accommodate new expressions. RBC could also face challenges in data privacy and ethical use, particularly with personal data from social media, necessitating careful navigation to prevent reputational and legal issues. Additionally, the bank needs to enhance its analytical tools to sift through large datasets efficiently to distinguish valuable insights from irrelevant noise to assess credit risk accurately.

Another solution is Word2Vec, a neural network-based, unsupervised learning method that learns vector representations of words from large text datasets. The vectors are designed so that

words with similar meanings are located close to one another in the vector space, which is beneficial for understanding relationships between words and extracting insights from textual data. RBC can analyze customer feedback to identify phrases like "financial struggle" and "assistance," which are closely clustered in vector space to proactively adjust credit risk assessments. When using Word2Vec to enhance credit risk analysis, key features could include:

1. Semantic Embeddings of Financial Terms: Word2Vec creates vector representations for words to capture their meanings based on the context where they appear. For credit risk, the terms could be related to financial health such as "bankruptcy."
2. Semantic Similarity Scores: Word2Vec assesses numerical similarity between words, linking terms like "financial crisis" with "bankruptcy" due to semantic closeness.
3. Contextual Grouping in Text: Word2Vec clusters contextually related words, which offers insight into common themes beyond individual word similarity.

Word2Vec offers advantages in understanding and analyzing language within financial contexts. Its primary strength is its ability to capture complex semantic relationships among terms, which provides a detailed comprehension of language nuances and captures semantic similarities. This feature becomes particularly useful for trend analysis when RBC can track how the associations between certain terms and credit risk evolve over time. This feature can be useful for identifying emerging risk factors or changing perceptions of an entity's financial health (Sandhu et al, 2022). Furthermore, Word2Vec's unsupervised learning approach significantly reduces the manual labour typically required to tag datasets, thereby simplifying the extraction of valuable insights from large volumes of text. Additionally, Word2Vec scales well with varying dataset sizes, making it a versatile tool for RBC, whether they are handling small or extensive textual data sources.

Despite its strengths, Word2Vec does have a drawback in its inability to handle out-of-vocabulary (OOV) words that are terms not present in its training data (Quantexa, 2024). This limitation hinders Word2Vec's effectiveness in environments where language is constantly evolving, as it cannot create embeddings for newly encountered words. Furthermore, the model's reliance on local context to define a word's meaning, while beneficial for capturing nuanced usage, can result in overlooking broader or abstract meanings. The challenges extend to multilingual applications. Adapting Word2Vec to new languages requires separate embedding matrices for each one, preventing the sharing of parameters and rendering the model less universally applicable(Quantexa, 2024). This could be a concern in Canada's multicultural context. Additionally, financial language is inherently ambiguous; words like "interest" may refer to monetary interest or general curiosity, which poses interpretation challenges when using Word2Vec to analyze financial documents.

Considering the information provided, sentiment analysis is recommended as the better solution for credit risk assessment. First, Sentiment analysis can directly assess the positive or negative sentiment in textual data, which can be more closely correlated with a borrower's perception of the market and, therefore, their creditworthiness. For real-time analysis, sentiment analysis stands out due to its ability to quickly adapt and respond to new information. This agility is particularly valuable in the financial sector, where the sentiment and public perception can shift quickly based on the latest news. Unlike Word2Vec, which cannot process new words that appear after the model training, sentiment analysis can incorporate the latest data through continuous updates or leveraging more flexible approaches. This ensures the analysis remains

relevant and reflects the current landscape to capture emergent sentiments that could impact credit risk assessments. Moreover, Sentiment trends can provide predictive insights into a borrower's future financial health by identifying shifts in public perception before they are reflected in financial statements or other lagging indicators. Although both solutions have advantages, sentiment analysis aligns more closely with the dynamic needs of credit risk assessment.

For conducting sentiment analysis for credit risk analysis at RBC, the most effective and ideal tools would depend on several factors, including ease of use, language support, performance, and integration capabilities with existing systems. NLTK (Natural Language Toolkit) has a comprehensive suite of libraries and tools for NLP in Python, which makes it highly adaptable for analyzing the sentiment of financial documents and customer feedback (Birjali et al., 2021). These libraries also offer a high degree of customization, allowing users to build and train their models from scratch or modify existing ones. Next, built upon NLTK, TextBlob simplifies many complex sentiment analysis tasks and provides a more user-friendly user interface for NLP tasks (Birjali et al., 2021). The ease of use and Python integration make TextBlob a great choice for rapid prototyping and integration into existing Python-based data analysis pipelines at RBC. Additionally, IBM Watson is a commercial, cloud-based AI and NLP services suite. With a user-friendly UI, it offers advanced sentiment analysis capabilities powered by deep learning and is able to understand complex financial documents (IBM Watson, n.d.). Its ability to integrate with RBC's existing systems and process data at scale makes it an ideal choice for enterprise-level sentiment analysis tasks. While both NLTK and TextBlob are open-source Python libraries available for free, IBM Watson comes at a cost. Overall, NLTK and TextBlob are best suited for users looking for open-source flexibility and customization. In contrast, IBM Watson offers enterprise-level, ready-to-use solutions with advanced capabilities and support, making it ideal for businesses seeking immediate, scalable insights without requiring extensive NLP or programming expertise. RBC's decision between these options will depend on whether it prioritizes quick deployment with ready-made tools or prefers to invest in developing sentiment analysis technology in-house.

Source Code Analysis

An information system that is critical to RBC’s digital client experience is the RBC online banking application. It serves as the primary interface for customers to engage with their bank accounts, make transactions, pay bills, transfer funds, and access a variety of financial services and products online and connects seamlessly to RBC’s data services and backend infrastructure. Given the vital role of software development in the delivery and implementation of RBC’s online banking system, the quality of the application source code directly affects client satisfaction and business performance, and should be rigorously tested using proper metrics. Metrics such as cyclomatic complexity, time complexity, and execution time serve as quantitative measures that can provide insights into the performance and characteristics of the codebase.

Cyclomatic Complexity & Cohesion Metrics

One metric that can be used to assess RBC’s source code is Weighted Method per Class (WMC), calculated by summing up McCabe's cyclomatic complexity, which measures the number of linearly independent paths of all local methods for each class. WMC was created as a

part of the suite of software metrics known as the Chidamber and Kemerer (CK) metrics and reflects the quality of the RBC's online banking system by measuring the complexity of its source code, where a higher number of complex methods makes it more likely to be difficult to understand, test, and maintain (Rebro et al., 2023). It provides a broad picture of complexity distribution of the source code by class and pinpoints areas for improvements. However, the significance of the WMC value can vary depending on the specific context of the system and its design: high complexity might be justified or even essential for certain core banking functionalities. As a result, WMC should be used in conjunction with cohesion metrics when measuring source code performance for the RBC banking app.

Given the complexity and feature-rich microservice system architecture of RBC's online banking app, it is likely that there is an extensive network of interactions between methods and attributes within classes in the application source code, which requires an advanced sensitive class cohesion metric to assess the quality and maintainability (Ibrahim et al., 2012). The sensitive class cohesion metric captures the different connections between classes and provides a more precise measure of source code cohesion, which can help refactoring efforts by pinpointing poorly designed classes, and ultimately enhance software maintainability and quality by promoting a more cohesive and modular design within application source code. However, collecting and analyzing this class cohesion metric would be challenging due to the complexity of accurately identifying and categorizing the interactions between class components and the vast amount of data in large software projects, which requires sophisticated tools to automate the analysis process.

A recommended tool for collecting WMC and class cohesion metric would be SonarQube. With its extensibility and comprehensive analysis capabilities, it can likely be configured to compute both metrics. In addition, SonarQube can be integrated into the source code management steps of RBC's DevOps pipeline so that whenever new code is committed to a repository, it can trigger an automated build analysis in SonarQube to ensure the changes are immediately evaluated for complexity and cohesion. With these two metrics combined, SonarQube can identify classes with high complexity and low cohesion, which might not necessarily be bugs (for example, it can be from containing too many unrelated functionalities) but lowers overall source code maintainability and makes it challenging for RBC developers to make future changes/bug fixes. To mitigate this, developers can refactor these classes to reduce complexity and improve cohesion, possibly by splitting them into smaller, more focused classes that each have a single responsibility to support a microservice architecture.

Time Complexity

Time complexity describes the computational complexity and the amount of computer time it takes to run an algorithm. As the input size changes, the execution time of the algorithm changes, reflecting the efficiency of the code (Papadimitriou, 2003). For the RBC banking app, a lower time complexity will mean faster transaction processing, quicker data retrieval, and an overall better performance of the app, leading to user satisfaction. Time complexity is expressed using Big O notation (e.g., O(n), O(log n), O(n^2)), removing constants and lower-order terms to focus on the algorithm's growth rate.

High time complexity algorithms can become bottlenecks in the system, especially if there are large data volumes, identifying these bottlenecks allow for targeted optimizations. Additionally,

time complexity helps in selecting the most suitable algorithm for a given problem, ensuring the balance between speed and resource consumption. Moreover, by analyzing time complexity, developers can predict how well an application will scale as the amount of data it needs to process increases. This is especially important for high-load applications, like the RBC banking application, where efficient data processing is critical.

Tools like SonarQube can be used for continuous inspection of code quality to identify inefficient code patterns that may affect time complexity. Furthermore, tools like SonarQube can be integrated during the Continuous Integration phase to automatically analyze and report inefficiencies in the code being pushed (Fabre, 2021). Developers may take corrective actions to handle these inefficiencies by refactoring or optimizing algorithms to ensure better data processing. This can be achieved by optimizing database queries or by either replacing the algorithm or minimizing its complexity.

Execution Time

Execution time is an important metric in assessing the quality of software, especially applications where speed and responsiveness are key, such as in banking apps. Execution time quantifies the duration required for a program to execute, serving as a direct indicator of the app's performance from the user's perspective. Faster execution times are synonymous with quicker responses to user requests, significantly enhancing the overall user experience by making the application more efficient and responsive. This contributes to user satisfaction as well as underscores the app's reliability and effectiveness in handling transactions and data processing tasks.

However, measuring and optimizing execution time has its own set of challenges. Factors such as varying hardware capabilities, fluctuating network conditions, and the unpredictable load on servers can introduce significant variability in execution times, complicating efforts to standardize and benchmark performance across different environments. Despite these obstacles, the benefits of focusing on execution time are manifold. It directly influences user satisfaction by improving the app's responsiveness, highlighting inefficiencies within the code or underlying infrastructure that can be optimized for better performance.

To accurately measure and analyze execution time, developers can utilize a range of profiling tools, such as JProfiler, Apache JMeter, etc. These tools are capable of assessing the execution time of different application components under varied conditions, providing valuable insights into the app's performance dynamics. Integrating these tools into the DevOps pipeline, particularly during the Continuous Integration phase, allows for the automated testing and monitoring of execution times. This integration facilitates the identification of performance bottlenecks under simulated load conditions, enabling teams to proactively address issues before they impact the user experience.

When profiling and performance testing reveal functions or components with excessive execution times, it prompts an investigation into the root causes. These could range from inefficient database queries and poorly optimized algorithms to infrastructure bottlenecks. Identifying these issues enables developers to take corrective actions, such as code optimization,

resource allocation adjustments, or database index restructuring, to enhance the app's performance.

The integration of execution time analysis into the DevOps pipeline embodies a strategic approach to continuous quality improvement. It ensures that performance considerations are integrated into the fabric of the development process, allowing teams to iteratively monitor and enhance the banking app's quality. This commitment to ongoing optimization culminates in a product that is not only more reliable and efficient but also offers a superior user experience, reflecting the high standards expected of modern financial applications.

Issue Management and Production Monitoring

The integration of Artificial Intelligence for IT Operations (AIOps) can significantly improve the efficiency and effectiveness of RBC's IT operations, especially in the context of their mobile banking app. AIOps leverages the power of artificial intelligence to automate and improve IT operations processes, including real-time monitoring, anomaly detection, and incident resolution, presenting innovative solutions for software quality and customer experience in mobile banking.

AIOps offers substantial benefits to RBC's IT team by automating routine monitoring and quality assurance tasks such as anomaly detection and failure prediction, to achieve high scalability and operational efficiency, allowing the team to concentrate on critical issues (Cheng, 2023). By continuously tracking and analyzing performance data, AIOps allows RBC to leverage predictive analytics to detect potential issues before they affect end-users. This helps developers and operational teams at RBC save time and resources on monitoring performance bugs and allows them to focus on developing anomaly prevention actions to mitigate IT issues to proactively avoid service disruptions (Zhao et al., 2021). In the case of bugs, AIOps helps operational and production teams process large-scale usage data from RBC's growing 1.9 million customer base and perform root cause analysis to identify underlying cause of incidents, facilitating efficient and accurate issue resolution at scale (Amazon Web Services, 2022). In addition, AIOps can accelerate incident resolution by diagnosing a predicted incident and automating recommended remediation actions, including temporary patches and long-term solutions accordingly. These decisions on which actions to take can be made with A/B testing and reinforcement learning algorithms to provide a dynamic strategy for resource management and workload balancing for RBC's IT teams (Cheng, 2023).

Despite the advantages, integrating AIOps into RBC's existing IT ecosystem presents several challenges. The complexity of integration requires significant time and resource investments, along with a need for high-quality, labeled data for AI models to function effectively. This might necessitate an overhaul of existing data management practices. Additionally, there may be cultural resistance within the organization as staff adapt to new workflows and place their trust in automated systems for decision-making. Given the sensitive nature of data processed and collected from the RBC banking app, another critical concern is ensuring the security and privacy of data used to train AIOps tools.

Monitoring metrics, such as system response times, system resource utilization (such as CPU usage), and error rates, play a crucial role in proactively identifying issues within RBC's

production environment (Reade, 2023). Real-time performance monitoring using these metrics enables the AIOps system to detect deviations from normal behavior, and send warnings for issues that require attention (Zhao et al., 2021). A practical demonstration of AIOps within RBC's mobile banking app could involve real-time monitoring to proactively predict and resolve issues. For instance, upon detecting a sudden increase in incoming request traffic, with a load balancer reporting a similar increase, AIOps will automatically predict issues such as transaction failures or degradation in response times, and will either add an additional virtual machine (VM) to re-route additional traffic, or send an alert for the production team to investigate this issue. This proactive approach minimizes user impact and potential downtime, showcasing the transformative potential of AIOps in banking operations.

The adoption of AIOps to monitor and resolve production issues has profound implications for end-users and RBC's business performance. On one hand, it creates more reliable and efficient services, enhancing trust in RBC's digital banking offerings. It also fosters innovation by freeing up human resources to focus on strategic initiatives. However, adopting AIOps poses major concerns regarding privacy risks, such as potential data breaches associated with AI accessing sensitive information such as customer data and financial transactions. As AIOps rely on high-quality data to train and produce accurate results, it raises the question of accountability when making automated production and resolution decisions based on machine collected, potentially erroneous or biased data. Lastly, the use of opaque and complex algorithms in AIOps often lead to decision-making processes that are not easily understood or reproducible, resulting in blind reliance on AIOps-controlled systems to dictate the trajectory of software development that gets integrated to millions of users' daily lives. These ethical and security concerns necessitate a balanced approach to AIOps integration that focuses on ensuring transparency, security, and fairness in AIOps tool design and implementation, which is crucial for RBC to strengthen IT security, maintaining customer trust and complying with regulatory standards.

The strategic adoption of AIOps by RBC represents a forward-thinking approach to navigating the complexities of digital banking, presenting opportunities to improve operational efficiency and customer service. However, integration challenges, ethical concerns, and the impact on organizational culture should be carefully considered before implementing AIOps to automate the production, monitoring, and resolution process of RBC's banking app. By addressing these issues head-on, RBC can leverage AIOps to not only enhance its operational capabilities but also secure a competitive advantage in the evolving financial services landscape, providing seamless digital banking experience for its customers while upholding security and privacy standards.

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