Fleetcor Cross-Sell Early Account Monitoring
6430_07_Group 3

Executive Summary

The Cross-Sell Early Account Monitoring project aimed to evaluate the performance and risk of early customers transitioning from the Fuel-Only Card to the Universal Card under the company's Cross-Sell Program. The project focused on assessing customer performance through financial metrics, transaction patterns, and overall behavior. By analyzing data such as credit utilization, repayment history, and spending habits, we identified key factors influencing customer success and engagement. The insights gained were used to refine the customer segmentation and targeting process, ensuring that the right customers were encouraged to transition to Universal Card.

Additionally, the project included a thorough transaction evaluation, which identified trends and patterns from past written-off accounts that could predict future risks. This analysis was essential for understanding the impact of transaction behaviors, such as frequency, timing, and platform usage, on customer performance. We developed a Cross-Sell performance dashboard using Power BI, which provided a comprehensive view of key metrics like delinquency rates, revenue generation, and spending behavior. This allowed stakeholders to monitor and analyze performance by portfolio, credit line increases (CLI), and other relevant criteria. Our risk assessment focused on identifying early signs of financial distress, such as late payments or high outstanding balances, to inform decision-making on necessary tightening treatments like account closures or credit limit adjustments. The project, which utilized tools such as SQL, ETL, R scripts, Excel, and Power BI, delivered actionable insights that contributed to optimizing the Cross-Sell Program and reducing the risk of write-offs.

Q1) Customer Performance Evaluation: The first step is to evaluate the financial performance of customers who have opted-in. This involves monitoring various key variables and metrics that provide insights into their credit card usage, repayment behavior, and overall financial health, etc. Utilize data analysis techniques, such as regression analysis, decision trees or CHAID, to evaluate various variables that strongly correlate with customer performance.

Solution: To evaluate the financial performance of customers who opted into the Cross-Sell Program, we analyzed key variables such as CLI amount, payment history, transaction volume, and credit utilization. These variables, including total spend, payment behavior, and the number of transactions, were found to strongly correlate with customer performance. By categorizing customers based on these factors, we provided the company with actionable insights into their financial health, enabling more accurate decision-making for future cross-sell strategies and identifying high-risk customers for proactive management.
a. The model used is **Random Forest** in **R**.

b. The top factors affecting the customer performance evaluation are **TOT_NET_REV**, **TOT_SPEND**, **TOT_NUM_TRX**, **FUEL_TRX_AMT**, and **TOT_TRX_AMT**.

c. The values for each factor are:

- **TOT_NET_REV**: 14.85 (Mean Decrease Accuracy), 59.73 (Mean Decrease Gini)
- **TOT_SPEND**: 5.17 (Mean Decrease Accuracy), 18.75 (Mean Decrease Gini)
- **TOT_NUM_TRX**: 5.10 (Mean Decrease Accuracy), 22.45 (Mean Decrease Gini)
- **FUEL_TRX_AMT**: 4.46 (Mean Decrease Accuracy), 9.80 (Mean Decrease Gini)
- **TOT_TRX_AMT**: 4.29 (Mean Decrease Accuracy), 19.93 (Mean Decrease Gini)

Q2) Transaction Evaluation: Analyze transaction data of past written-off Cross-Sell accounts and identify transaction-related variables and patterns which have predictive value for future performance of early Cross-Sell customers. Variables and patterns may include transaction platform, transaction completed in certain time frame, etc.

Solution: To assess the transaction valuation requirements for Cross-Sell accounts, analyzed historical transaction data from written-off Cross-Sell accounts to identify key patterns and features that predict default risk. By employing advanced modeling techniques, it evaluates the impact of transaction behaviors and timeframes on future performance. The insights gained enable the company to develop targeted strategies for managing early Cross-Sell customers

a. The model used is **XGBoost** in **R**
b. By examining historical transaction data, the top factors influencing this assessment include **WO_AMOUNT**, **LOCK_REASON**, and **SEGMENT_SCORE**. WO_AMOUNT is particularly critical, as it represents the write-off amount; higher values indicate a greater financial risk, with accounts showing substantial write-offs being more likely to default. The LOCK_REASON provides insight into the underlying issues that may lead to account locks, which can correlate with management problems or other risk factors that elevate the likelihood of default. Lastly, the SEGMENT_SCORE offers a nuanced risk assessment based on various account characteristics
c. WO_AMOUNT values were shown to have a significant influence, with a maximum gain of approximately **0.997**, indicating that accounts with higher write-off amounts are more likely to default. The **LOCK_REASON** factor had a gain of about **0.0027**, suggesting that while it is a less dominant factor compared to **WO_AMOUNT**, it still plays a role in requirement. Lastly, the **SEGMENT_SCORE** had a minimal gain of approximately **0.000155.**

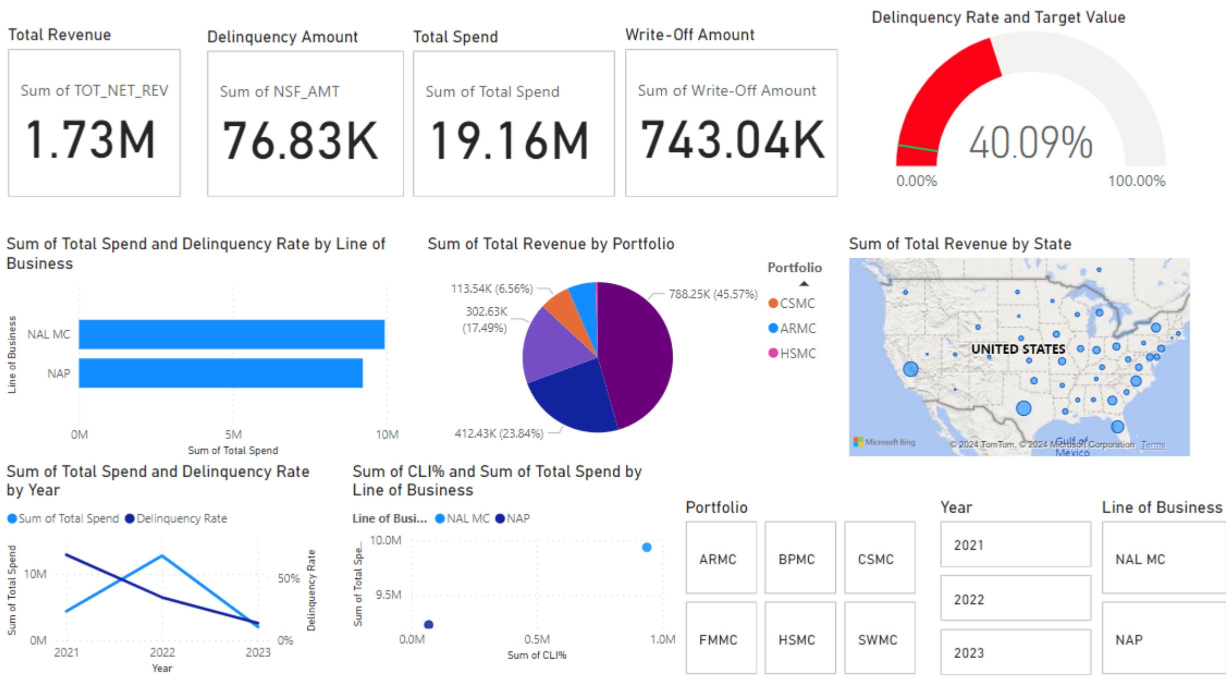
Q3) Risk Assessment: The report aims to assess the level of risk associated with these customers. By analyzing key variables, it becomes possible to identify potential signs of financial distress or credit risk. This includes looking at factors such as outstanding balances, late payments, credit utilization, and any delinquent indicators.

Solution: Analyze key variables such as outstanding balances, late payments, credit utilization, and delinquent indicators to identify potential signs of financial distress or credit risk among customers. This analysis will help in determining their overall risk levels effectively.

a. The model used is **Logistic Regression** in **R**.
b. The top factors affecting risk assessment include **CLI_AMOUNT**, which indicates credit limits and outstanding balances; **TOT_SPEND,** reflecting total customer spending; and **NSF_PMTS**, which signals potential financial distress through non-sufficient funds payments. Additionally, the **PAYDEX** score highlights payment history, with lower scores indicating higher risk, while **Credit_Utilization** assesses how much of their credit limit is being used, providing further insights into the customer's financial behavior and risk profile.
c. The values for each factor are:

- **CLI_AMOUNT: -2.027e-04**(Higher credit limits decrease the likelihood of being classified as high risk.)
- **TOT_SPEND: 1.572e-03**(Increased total spending raises the likelihood of being classified as high risk)
- **NSF_PMTS: -5.385**(More non-sufficient funds payments strongly increase the risk classification, indicating significant financial distress)
- **PAYDEX: 2.580e-02**(A better payment history (higher PAYDEX) slightly increases the risk classification)
- **Credit_Utilization: 5.181e+02**(High credit utilization dramatically increases the likelihood of being classified as high risk)

Q4) Create a Cross-Sell performance dashboard: Show performance data (delinquency, write-off, spend, revenue, etc.) in different views, such as by line of business, portfolio, CLI%, opt-in date, etc.
Solution: The dashboard provides a comprehensive view of the Cross-Sell program's performance, enabling Fleetcor to monitor and analyze key indicators like delinquency, write-offs, spending, and revenue across different business lines and portfolios.
a. The Tool used is **PowerBI.**



Q5) Decision-Making: Based on the analysis of customer performance and risk assessment, the report will provide a basis for making decisions regarding tightening treatments and potential financial impact (in revenue and write-off) to mitigate the risk. These treatments may include inactive account closure, credit limit decrease, term tightening.

Solution: The company should focus on high-risk customers by implementing tighter controls such as monitoring payment frequency, reducing credit limits, and tightening terms. These decisions will help mitigate financial risks, minimize write-offs, and protect revenue. Treating these high-risk customers effectively will prevent further losses and ensure better financial stability.

High_Risk_Customers (1).xlsx

a. The model used is **Random Forest** in **R**

b. Based on the analysis, the top factors influencing risk include Total Net Revenue **(TOT_NET_REV)**, Number of Payments **(NO_OF_PAYMENT)**, **PAYDEX** score, Write-Off Amount **(WO_AMOUNT)**, and Non-Sufficient Funds Payments **(NSF_PMTS)**.

c. The values for each factor, **Total Net Revenue (TOT_NET_REV)** is the top factor, with a score of about **60**, suggesting more frequent payment monitoring to maintain revenue. **Number of Payments (NO_OF_PAYMENT)** comes next, with a score of around **10**, showing the importance of keeping track of payment habits. **PAYDEX**, scoring about **5**, points to the need for credit monitoring or adjusting terms for customers with low credit scores. **Write-Off Amount (WO_AMOUNT)**, with a score of around **3**, suggests focusing on accounts that need collection or recovery efforts. Finally,

Non-Sufficient Funds Payments (NSF_PMTS), scoring about **2**, supports the idea of closing inactive accounts to reduce risk.

Main Section

a. The data integration performed, including data modeling, and data preparation.

The success of the Cross-Sell Early Account Monitoring project heavily depended on effective data integration and preparation. The objective was to consolidate data from multiple sources, transform it into a structured format, and prepare it for advanced analysis and predictive modeling. Below are the steps and techniques employed in the data integration and preparation process:

Review and Assessment of Raw Data

The provided raw dataset consisted of **29,410 rows** of Cross-Sell customer data. This large volume of data posed potential processing challenges, prompting the decision to work with an initial subset of **500 accounts**, sorted by the FAKE_ACCTCODE field. This allowed us to streamline the process while maintaining a representative sample for initial analysis.

Data Integration Using ETL Process

The integration of data was carried out using **SQL Server Integration Services (SSIS)** within Visual Studio. This process included the following key steps:

Extraction:
Data was imported from Excel spreadsheets using the SSIS **Import and Export Wizard**, ensuring a seamless transfer into the database.

Transformation:
Key transformations were applied to enhance the usability and quality of the data:

- **Aggregate Transformation:** Calculations such as grouping, summing, and averaging were performed to generate aggregated insights.

Loading:
The processed data was loaded into the **Fleetcor_Database** on SQL Server, ensuring a centralized and structured storage environment.

SSIS Components Used:

- **Source Assistant** for importing data.
- **Aggregate Actions** for performing transformations.
- **Destination Assistant** for storing transformed data in SQL Server.

Data Consolidation and Preparation

Post-integration, the dataset underwent rigorous preparation to make it analysis-ready:

- **Table Joins and Schema Design:**
  Using **Primary Keys (PKs)** and **Foreign Keys (FKs)**, related tables were joined to create a comprehensive, normalized schema.
- **Union and Deduplication:**
  Union operations were applied to merge data from multiple sources. Duplicate entries were identified and excluded to ensure data accuracy.
- **Null Value Handling:**
  Null values were flagged for handling during the modeling phase in R. This ensured the dataset's consistency without discarding potentially valuable information.

b. The details about the models and tools used to obtain predictions and the rationale for choosing the model which for the predictions made.

The Cross-Sell Early Account Monitoring project utilized a combination of predictive models and tools to derive insights and inform decision-making. For customer performance evaluation, the **Random Forest** model in R was chosen due to its ability to handle large datasets, manage complex relationships, and identify variable importance. This model was particularly effective in highlighting key drivers of customer behavior, such as revenue, transaction patterns, and credit utilization. For transaction evaluation, **XGBoost** was employed because of its efficiency in handling imbalanced data and its ability to uncover critical transaction-related variables, such as write-off amounts and account lock reasons, which were strong predictors of future risk. Additionally, **Logistic Regression** was selected for risk assessment due to its simplicity and interpretability, allowing for a clear understanding of how variables like credit utilization and non-sufficient funds payments impacted the likelihood of default.

The tools used to support these models included **R** for advanced analytics, **SQL Server** for data integration and preprocessing, and **SSIS** for streamlining ETL workflows. **Power BI** was instrumental in visualizing key performance metrics, enabling stakeholders to monitor delinquency rates, revenue trends, and spend behaviors effectively. The selection of these tools and models ensured accurate predictions, actionable insights, and transparency in the decision-making process, aligning with the project's objectives of optimizing the Cross-Sell Program and mitigating financial risks.

Conclusion: The Cross-Sell Early Account Monitoring project represents a strategic breakthrough in financial risk management and customer portfolio optimization. Through rigorous data analysis, we uncovered critical insights into customer performance, identifying key financial indicators that drive successful Universal Card transitions. Our comprehensive approach revealed nuanced patterns in revenue generation, transaction behaviors, and credit utilization, enabling precise risk assessment and targeted intervention strategies. By developing a sophisticated framework for identifying and mitigating potential financial risks, we established a proactive methodology for managing cross-sell account performance. The project not only provides actionable recommendations for tightening treatments like account closures and credit limit adjustments but also creates a robust, data-driven foundation for future cross-selling initiatives.

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