Commercial Banking Corporation: Retail Credit Scoring

BLUE TEAM 10
Tre Hill
Suyeon Kim
Ava Konopka
Patrick Moore
Ben Poovey

January 24, 2025

Table of Contents

COMMERCIAL BANKING CORPORATION: RETAIL CREDIT SCORING

Overview

The Commercial Banking Corporation (hereafter referred to as "the Bank") tasked our team with creating a scorecard to evaluate retail credit applications. Our analysis prioritized maintaining the current acceptance rate of 75% while minimizing default rates. In doing so, we determined that the optimal score cutoff was 510 points. The reason for this is threefold: it maintains the current acceptance rate at 75%, reduces the default rate to 2.10%, and generates approximately $31 million of profit for the Bank. Because of this, we affirm that implementing this cutoff will best match the Bank's long-term objectives.

Methodology and Analysis

This section outlines the data and modeling process used to create the scorecard for evaluating retail credit applications.

Data

We used two datasets in the scorecard creation process. The first contained 3,000 observations describing accepted applicants, and the second contained 1,500 observations describing rejected applicants. Both datasets contained 22 predictor variables describing the attributes of the applicants. The accepted dataset was balanced with 1,500 "good" and 1,500 "bad" applicants, where "bad" was defined as a loan payment that is 90 days past due once. The target variable within the accepted dataset yielded a value of one if the applicant was considered "bad" and a value of zero to describe "good" applicants. Before building our model, we randomly split the accepted dataset into 70% training and 30% validation. We also removed the age and nationality variables to avoid regulatory or ethical issues. Finally, we imputed missing values with a new "missing" category.

Scorecard Model

We first focused on optimally binning the continuous variables in the accepted dataset. Before binning, we removed the credit bureau risk class, EC card holder, and region variables as they were highly correlated with other variables in our data. We then performed variable selection by removing variables with an information value below 0.1, keeping only those with a strong ability to predict the target. This left us with four variables: income, type of credit card, time at job, and number of persons in the household. Next, we built the behavioral scorecard, assigning a base score of 500 to applicants with odds of acceptance 20 times higher than rejection. Additionally, we set a 50-point change in the score to represent a doubling of the odds. To reach the actual "bad" rate of 3.23%, we used the weight variable included in the dataset to adjust for over-sampling.

As the Federal Deposit Insurance Corporation (FDIC) required, we developed a more generalized scorecard using reject inference with the hard cutoff augmentation approach. We determined that 0.04 was the optimal cutoff for our behavioral scorecard. Thus, any prediction above 0.04 was classified as a "bad" applicant, while the rest were considered "good." To create our combined dataset, we added only the first 1000 rows from the scored rejected data to the accepted data to maintain the actual 75% accepted and 25% rejected balance. After building the final scorecard, the area under the curve (AUC) was used to evaluate model performance, and both decile and trade-off plots were used to determine scorecard cutoffs.

Results

Our final model had an AUC of 0.76 with an optimal cutoff point of 0.04, as displayed by the receiver operator characteristic (ROC) curve in Figure 1.

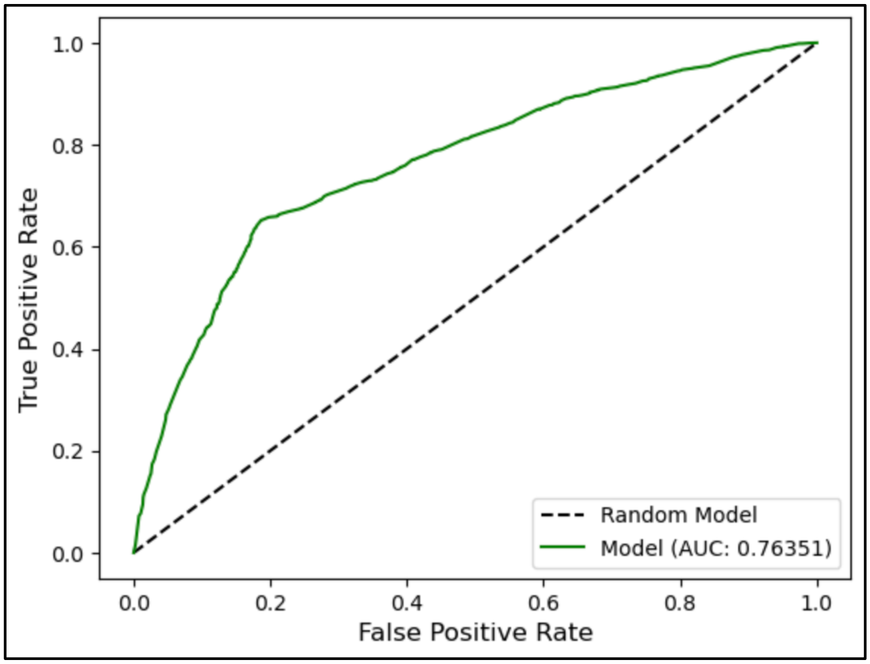

Figure 1: Final Model ROC Curve

The AUC of 0.76 indicates that, on average, the model assigned higher predicted probabilities to “bad” customers than to “good” customers approximately 76% of the time, reflecting a moderately strong ability to differentiate between the two groups. Another way to evaluate model performance is through the decile plot in Figure 2, which bins the predicted scores from the validation dataset into ten equal pieces.

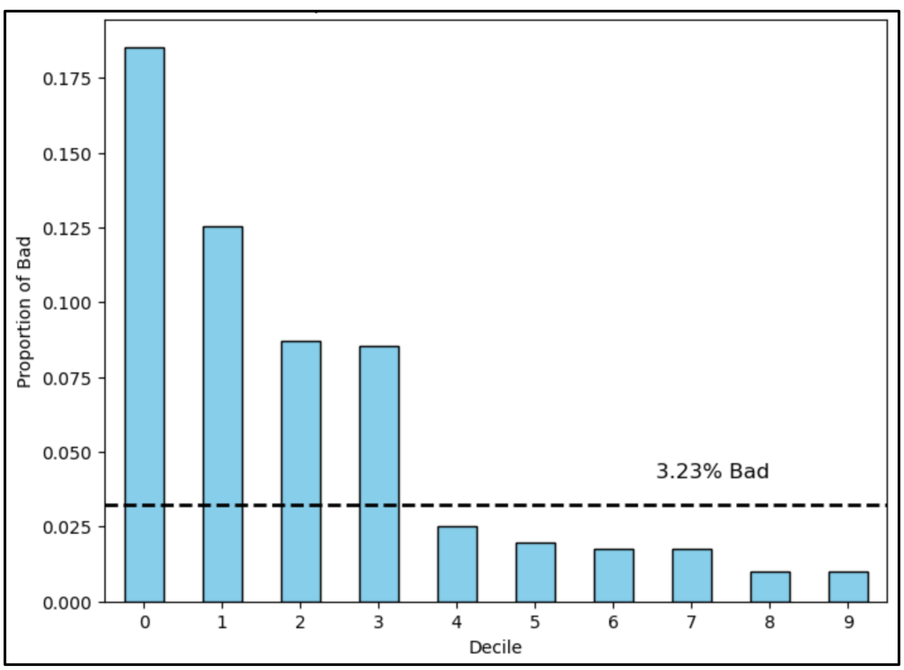

Figure 2: Proportion of “Bad” Applicants Across Deciles of Score

As scores increased, “bad” applicant rates monotonically decreased, indicating that the model effectively identified and ranked customers by their likelihood of being a “bad” applicant.

We examined two tradeoff plots to determine the best cutoff points for our scorecard. The first plot, displayed in Figure 3, compared the acceptance rate with the rate of "bad" applicants across different score cutoffs.

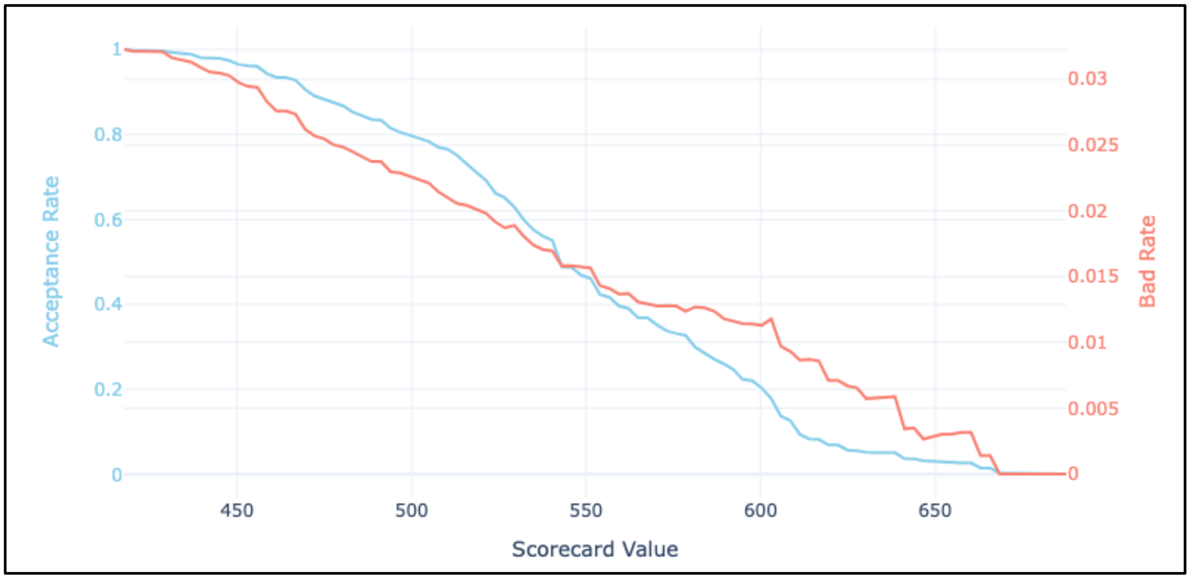

Figure 3: Acceptance and "Bad" Applicant Rates Across Score Cutoffs

To maintain the current acceptance rate of 75%, we recommend that the Bank accept applicants with a score of 510 or higher. This also reduces the "bad" applicant rate to 2.10% from the current rate of 3.23%. The second tradeoff plot compared the acceptance rate against the profit across different score cutoffs, as displayed in Figure 4.

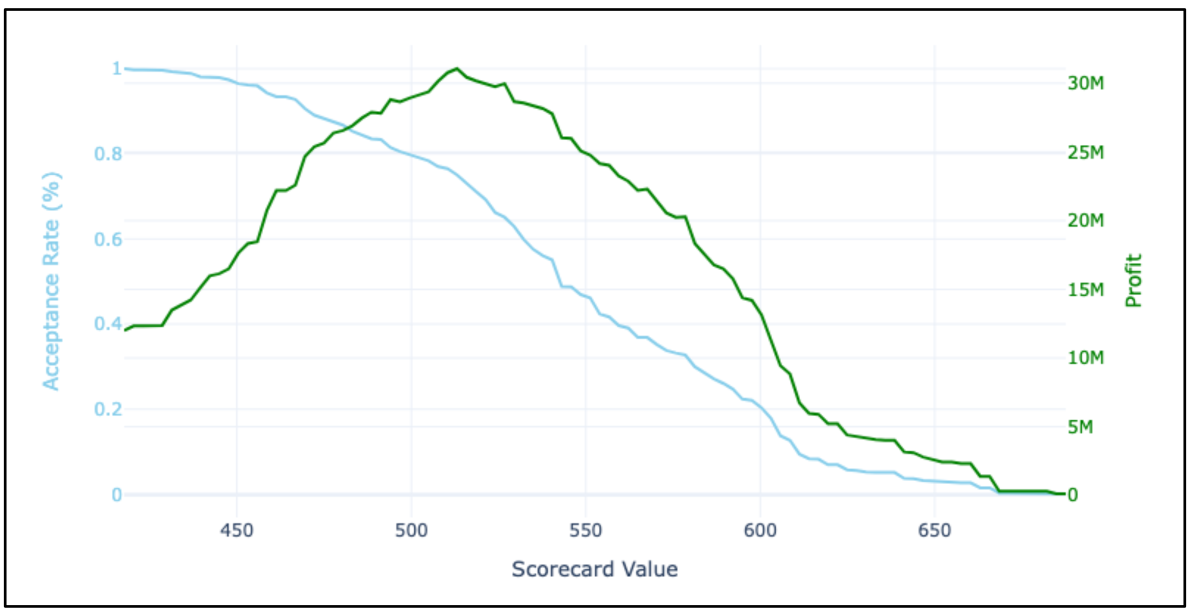

Figure 4: Acceptance Rates and Profit Across Score Cutoffs

To maximize profit, the Bank should accept applicants with a score of 510 or higher. This would result in a profit of about $31 million for the Bank while aligning with the Bank's 75% acceptance rate.

Recommendations

Based on the analysis we've conducted, we recommend that the Bank take the following actions:

- **Implement a cutoff of 510**: The Bank should implement a cutoff of 510. This ensures they maintain their acceptance rate while reducing the "bad" applicant rate. This cutoff would also yield a maximum profit of $31 million.
- **Continue to monitor economic conditions**: We recommend that the Bank adjust its scorecard parameters by consistently tracking economic trends and consumer behavior. This proactive approach will help manage credit risk effectively while maintaining optimal acceptance rates.
- **Target clients likely to maximize profits**: The Bank could market available loan options by primarily targeting clients with scores between 510 and 612. Clients within this range are more likely to help the Bank maximize their profits.

Conclusion

Our team developed a behavioral scorecard model to evaluate retail credit applications. The model identified key predictors, including income, type of credit card, time at job, and household size, as significant contributors to applicant risk profiles. The finalized scorecard achieved an AUC of 0.76, demonstrating strong predictive performance and reliable discrimination between "good" and "bad" applicants.

By implementing a cutoff score of 510, the Bank can maintain its acceptance rate of 75%, reducing the "bad" applicant rate from 3.23% to 2.10%. This strategy is projected to generate approximately $31 million in profit. Based on these results, we recommend adopting the 510 cutoff and monitoring economic trends for periodic scorecard adjustments. Targeted marketing to high-score applicants can further enhance profitability and customer engagement. These measures will enable the Bank to effectively manage credit risk, optimize acceptance rates, and maximize financial outcomes.