# RETAIL CREDIT SCORING


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# RETAIL CREDIT SCORING

## Overview

The Commercial Banking Corporation (the Bank) has engaged Blue Team 13 to create a comprehensive scorecard and associated score buckets for evaluating all retail credit applications. This scorecard will be a key tool used by the Bank to assess the creditworthiness of retail customers and make critical decisions about approving credit applications.

The final scorecard is built on the following set of variables:

- Age of the customer (AGE)
- How long they have worked at their job (TMJOB1)
- Number of persons in the household (PERS_H)
- Credit cards (CARD)

The team also created a distribution to associate score buckets with default rate which helps the Bank better understand the risk associated with different credit scores and make more informed decisions about lending. Using Blue Team 13's final scorecard with the created score buckets, the Bank will maximize profit to $33M at an acceptance rate of 61% while lowering the default rate to 1.58%.

## Methodology & Analysis

### *Data Preparation*

There were two datasets provided by the Bank, each for accepted and rejected customers, containing 3000 and 1500 observations, respectively. These datasets listed 22 features of the customers that provided information about their demographics, assets, liabilities, and past credit history in addition to the target variable. The target variable represented the good customers (who did not default) as 0 and the bad customers (who defaulted) as 1. As per the Bank's suggestion, 70% of the accepted customers' data was randomly sampled as the training dataset, while the rest was considered the validation dataset.

The information value (IV) for every variable in the training dataset was calculated using an optimal binning strategy to prepare it for modeling. Six variables reported an IV of 0.1 or more, thus significant for the modeling step. Of these variables, the numerical variables were converted to the necessary bins using the same binning strategy to be treated as categorical values. The CARDS variable had a quasi-complete separation problem with the target variable. To resolve this, we binned the problematic levels, namely "American Express," "VISA mybank," and "VISA Others," into the "Other credit car" level in both the original datasets. Once all the variables were converted to categorical variables, the Weight of Evidence (WOE) values were calculated and used as inputs for building an initial model.

### *Initial Scorecard Creation*

We built a logistic regression model, i.e., the initial model using the WOE values calculated for the six variables from the training dataset to build an initial scorecard. The significant variables reported from this initial model were AGE, TMJOB1, PERS_H, CARD, EC_CARD, and INCOME (which represents the member's income). To adjust the number of sampled "reject" cases to accurately reflect the number of reject cases from the population, the weights for the good and bad customers were also provided to this model. This initial logistic regression model reported an area under the receiver operating characteristics curve (AUROC) value of 0.7189 on the training dataset. After assessing the performance of this model on the validation dataset, the reported AUROC value was 0.6847.

### *Reject Inference*

As per the Federal Deposit Insurance Corporation's (FDIC) regulatory compliance requirement to conduct reject inference, our team chose the Parceling Augmentation method. As a first step in this process, we divided the final score, which ranged from 400 to 700, into 30 equal bins. For every bin, the rejected customers observed in that bin were randomly assigned as good or bad while maintaining their ratio from the accepted customers' dataset. We then used the initial scorecard model to calculate the scores for these rejected customers to create a final scorecard.

### *Final Scorecard Creation*

After calculating the scores for the rejected customers, we combined the datasets for accepted and rejected customers, including their scores. Using this combined dataset, we built a logistic regression model to construct the final scorecard using the WOE values and coefficients from the model's output for each variable included.

## Results

The five variables that both report IV greater than 0.1 and were used to build the final logistic regression model are below

- Age of the customer (AGE),
- How long they have worked at their job (TMJOB1),
- Number of persons in the household (PERS_H),
- Credit cards (CARDS)
- EC card holder (EC_CARD)

Among the five variables, the first four variables were statistically significant in the model except for EC_CARD. However, our team also found that EC_CARD is highly correlated with CARDS. Thus we removed EC_CARDS after the final model reported an AUROC value of 0.7173 for the training dataset and a value of 0.6919 for the validation set.

## *Final Scorecard*

**Table 1** represents the final scorecard we built using the four variables identified in our final model and their associated points for each level. An applicant receives points based on which level they fall into, and the points are summed across all variables to calculate the total score. The total score will determine whether or not the Bank will give the loan. For instance, an applicant who is older than 45 (148.6782 points), spent 28 days at their job (94.8443), lived in a 4-person household (119.0705), and owned a Cheque card (151.0562), would have a total score of 513.6492. If the Bank were to use a cutoff value of 500 theoretically, the applicant would be given the loan.

**Table 1: Final Scorecard**

| Variable | Level | Scorecard Points |
|---|---|---|
| Age | $0 \leq x \leq 22$ | 59.8649 |
| Age | $23 \leq x \leq 27$ | 81.1045 |
| Age | $28 \leq x \leq 45$ | 115.5265 |
| Age | $x > 45$ | 148.6782 |
| Time at Job | $0 \leq x \leq 9$ | 77.2662 |
| Time at Job | $10 \leq x \leq 30$ | 94.8443 |
| Time at Job | $31 \leq x \leq 84$ | 105.1758 |
| Time at Job | $85 \leq x \leq 216$ | 129.2534 |
| Time at Job | $x > 216$ | 156.1195 |
| Number of People in Household | $0 \leq x \leq 1$ | 83.3082 |
| Number of People in Household | $2 \leq x \leq 4$ | 119.0705 |
| Number of People in Household | $x > 4$ | 106.0355 |
| Credit Cards | Cheque Card | 151.0562 |
| Credit Cards | Mastercard/Euroc | 159.4963 |
| Credit Cards | No Credit Cards | 89.6092 |
| Credit Cards | Other Credit Card | 123.3067 |

Based on the table above, and **Figures 6 and 7** in the Appendix, the score points increase with the increase of age for customers while the default rate decreases. The score and default rate have similar trends for customer time on the job, which logically makes business sense.

## *Distribution of Scores - Decile Plot*

**Figure 1: Default Decile Plot** on page 4 illustrates the distribution of associated score buckets for default rate. The plot shows the default rate in each one of those ten groups of the score. The dashed line on the graph represents the current population default rate of 3.23%, indicating the bank's current cut-off score of 525. Customers who score below 525 are more likely to default, while those with a score higher than 525 are less likely to default.

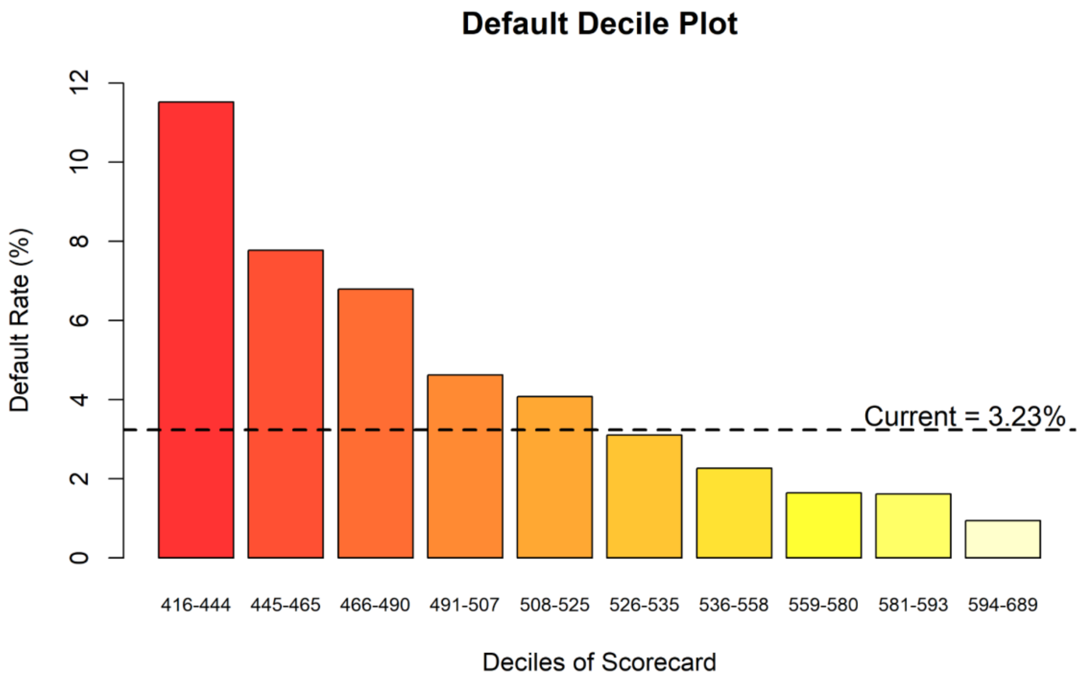


**Figure 1: Default Decile Plot**

While the model provides an optimal cutoff value using a classification matrix, other cutoffs can be investigated by viewing the associated acceptance and default rates across scorecard values. As shown in **Figure 4** in the Appendix, a default rate of 2.12% will maintain the Bank's existing acceptance rate of 75%, with a scorecard cutoff value of 506. Balancing the loan acceptance rate and potential profit can also determine a cutoff level. From **Figure 5** in the Appendix, the Bank can maximize its profit using a cutoff value of 533, equating to a 61% acceptance rate.

# Recommendation

Utilizing our scorecard yields a maximum profit of $33M for the Bank at a lower acceptance rate of 61% and lower default rate of 1.58%. If the Bank sticks with a preferred acceptance rate of 75%, giving a default rate of 2.12%, the profit earned will be approximately $2M less than what can be earned utilizing a 61% acceptance rate with Blue Team 13's scorecard. Therefore, based on the results detailed in this report and the Bank's ultimate goal of assessing customer creditworthiness, our team recommends implementing our scorecard (detailed in **Table 1** on page 3) to **maximize revenue** while simultaneously **lowering** the Bank's **current default rate** of 3.23%.

# Conclusion

Overall, this analysis is an important step forward in helping the Bank manage credit risk and make sound lending decisions. By using Blue Team 13’s scorecard, the Bank will make more accurate and reliable assessments of each customer's creditworthiness and better understand the risk associated with different credit scores. This will ultimately help the Bank reduce its credit risk, increase its lending efficiency and maximize the company's overall profit.

# Appendix

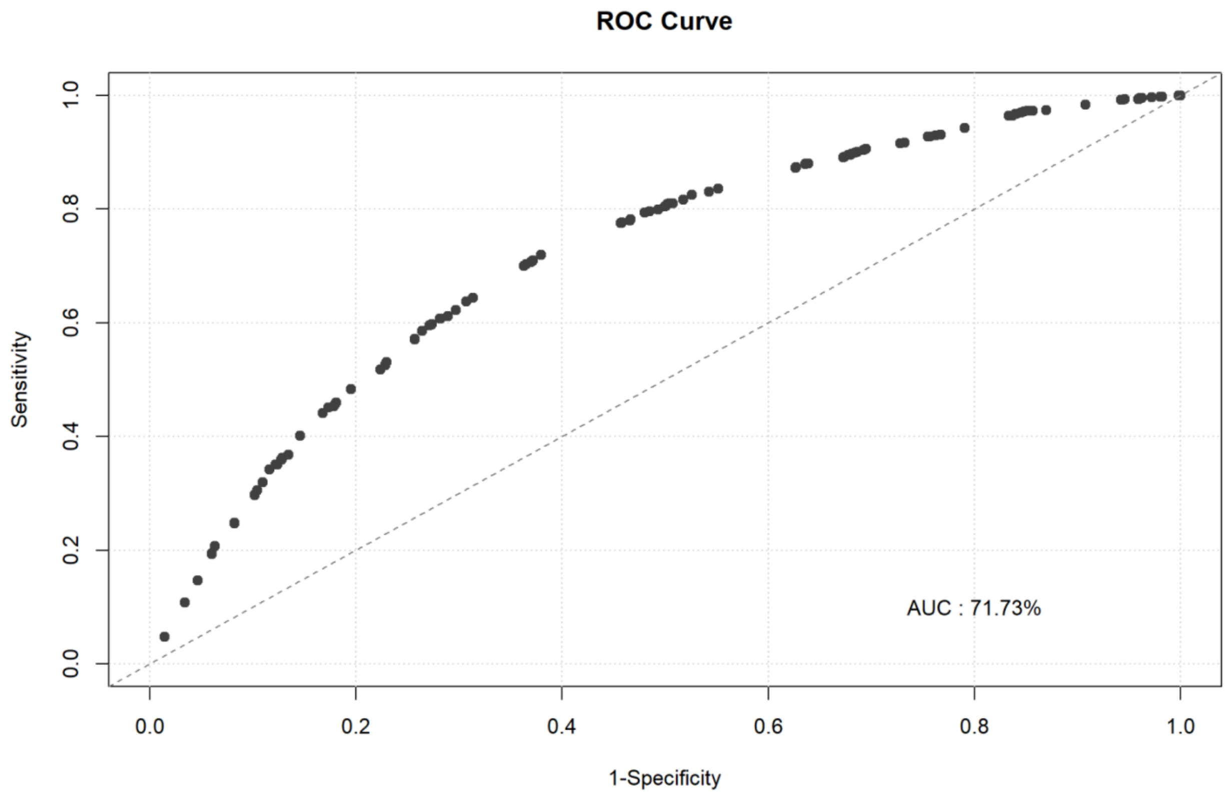


**Figure 2: ROC plot for the final model**

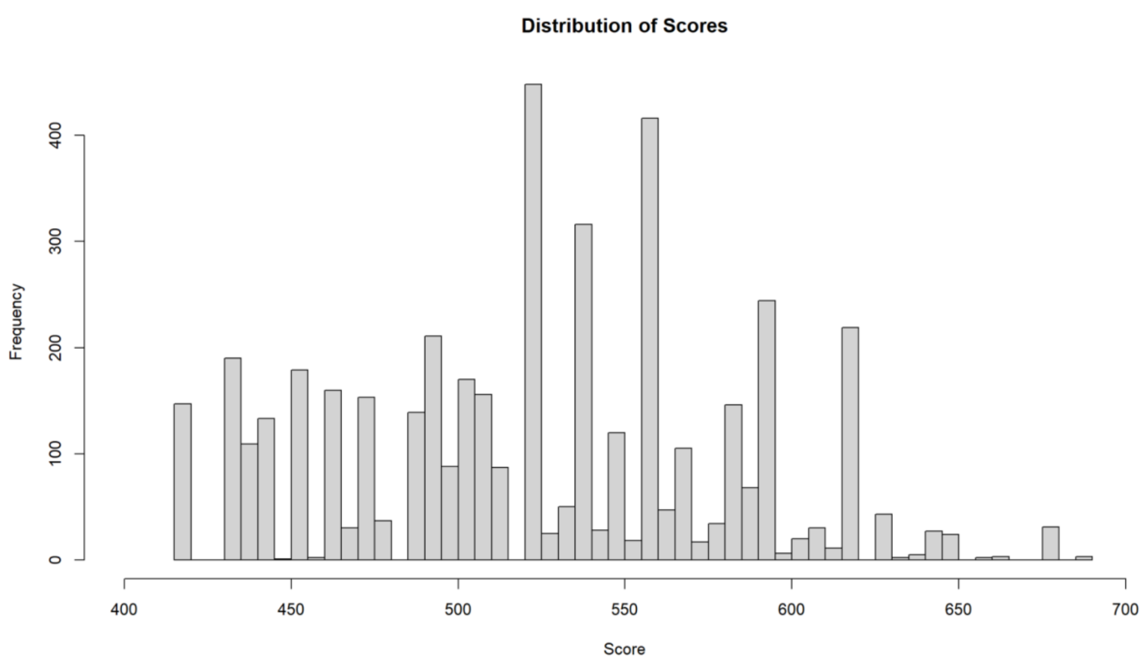


**Figure 3: Distributions of Scores from training set**

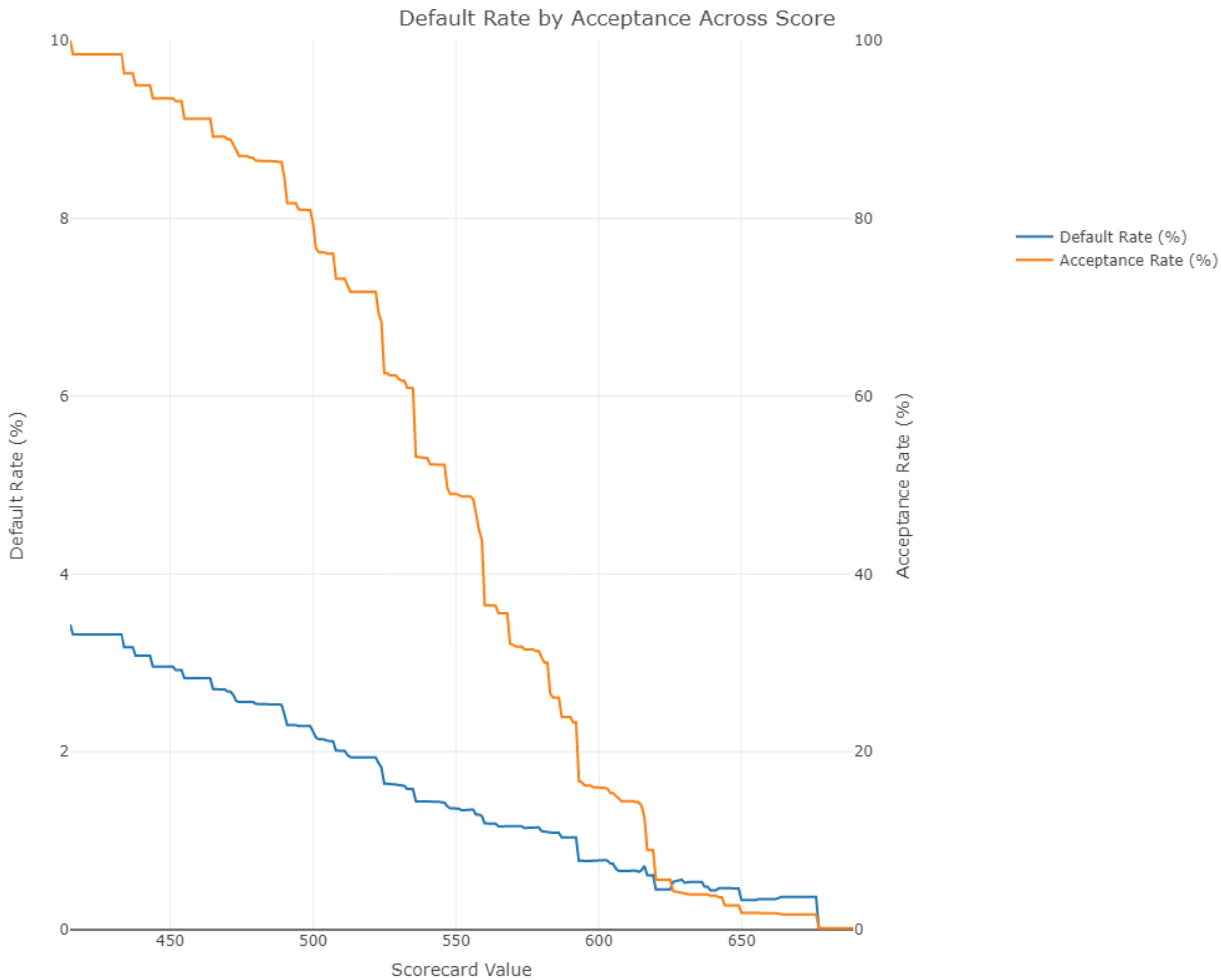


**Figure 4: Default rate by acceptance across score**

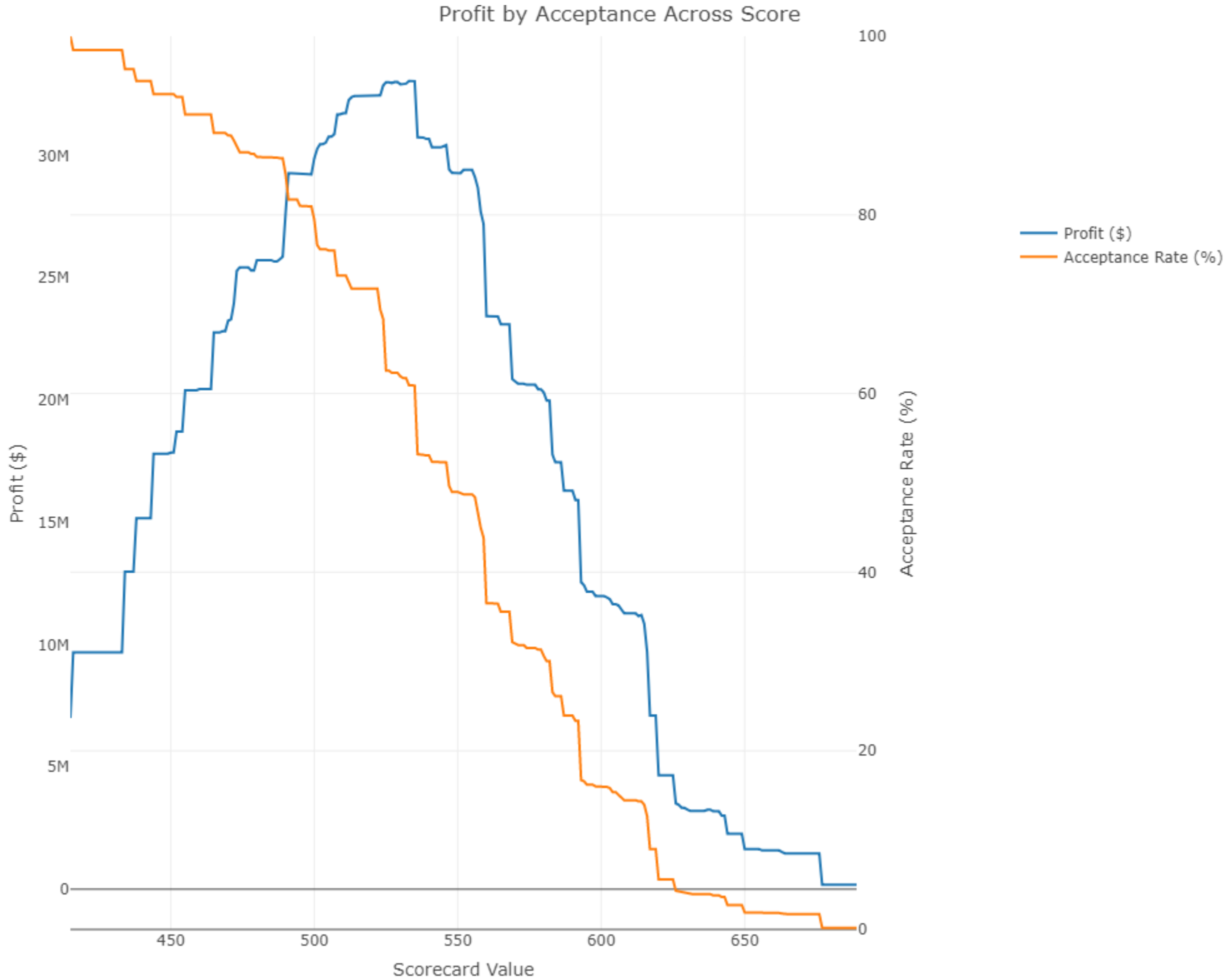


**Figure 5: Profit by acceptance rate across score**

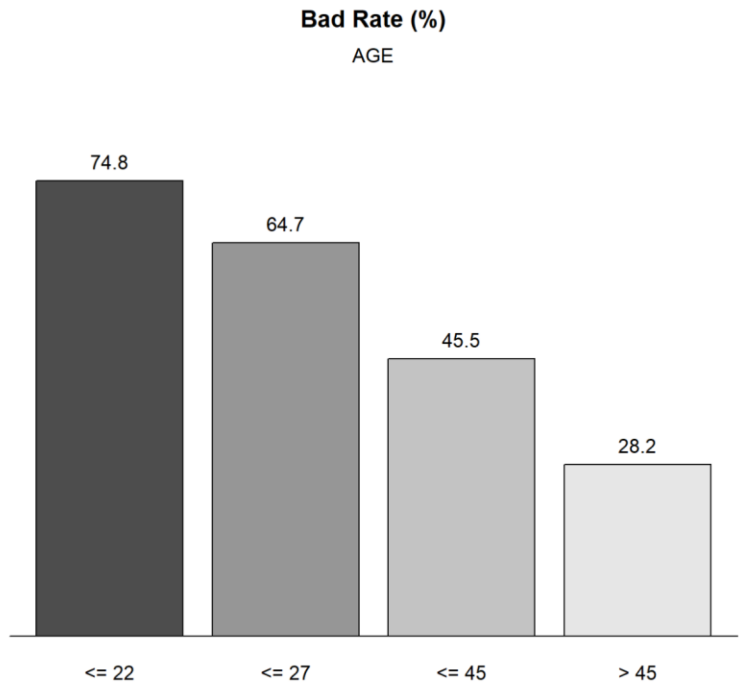


**Figure 6: Default rate for AGE**

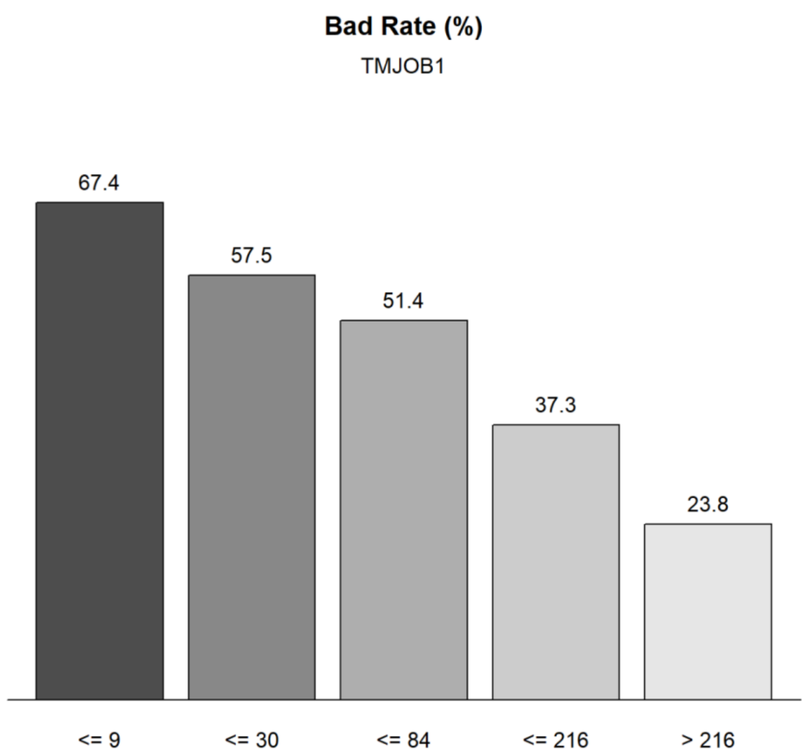


**Figure 7: Default Rate for Time at Job**

# Homework Report Checklist

The team member(s) responsible for checking each item should enter their initials in the field next to each question. All items should be addressed before submitting the assignment with the initialed checklist attached.

Sections & Structure

Overview

| | |
|---|---|
| MD | Is the overview concise? |
| MD | Does it provide context about the business problem? <Content> |
| MD | Does it briefly address your team's work, quantifiable results, and recommendations? <Action> |
| MD | Does it offer audience-centered reasons for recommendations? <Context> |

Body Sections

| | |
|---|---|
| SS | Does the report body include information on methods, analysis, quantifiable results, and recommendations? |
| SS | Is content grouped into appropriate sections (*methodology*, *analysis*, *results*, *recommendations*)? |

Conclusion

| | |
|---|---|
| MD | Does the report have a conclusion? |
| MD | Does the conclusion sum up the report and emphasize relevant takeaways? |

Structure

| | |
|---|---|
| SS | Does each major section have a heading? |
| SS | Are sections, subsections, and paragraphs organized logically for easy navigation? |

Visuals

Introduction, Discussion, and Captions

| | |
|---|---|
| PJ | Is each visual introduced in the text before it appears? |
| PJ | Is each visual close to where it is introduced? |
| PJ | Does each visual include a title with the following information: type (*table* or *figure*), number, and a descriptive caption? |
| PJ | Is each visual discussed and interpreted in the text? |
| PJ | Are figures and tables numbered separately? |
| PJ | Are table captions above the table? Are figure captions below the figure? |

Visual Design

| | |
|---|---|
| DS | Do figures/tables use audience-friendly labels rather than variable names? |
| DS | Are the visuals easy to interpret? |
| DS | Are the visuals appropriately sized? |
| DS | Do tables appear on one page (*not split between 2 pages*)? |
| DS | Are legends and axis labels included for figures? |
| DS | Are numbers in tables right aligned? |
| DS | Are the visuals designed well (*ex*: *re-created in Word or Excel*, *not blurry or stretched*,…)? |

## Document Design

### Title Page Design

| | |
|---|---|
| PJ | Does it include a descriptive title? |
| PJ | Does it state the team name, team members' names, and the submission date? |

### Table of Contents Design

| | |
|---|---|
| DS | Does it list all the major sections of the report with corresponding page numbers? |
| DS | Do the page numbers and sections in the Table of Contents match the report? |

### **Document Design for Entire Report**

| | |
|---|---|
| DS | Is a standard typeface (*Calibri*, *Arial*, *etc.*) used? |
| DS | Is the size of the body text between 10-12 pt.? |
| DS | Are headings and subheadings used to organize information? |
| DS | Are distinctive text styles (*bold*, *italic*, *etc.*) used to distinguish between heading levels? |
| DS | Are text styles for headings used consistently (*ex*: *all level-one headings are bold*)? |
| DS | Are all paragraphs an appropriate length (*fewer than 12 lines*)? |
| DS | Is white space used to indicate paragraph breaks? |
| DS | Are bullet lists used for a series of items and numbered lists to show a hierarchy? |

## Writing Style and Mechanics

### Spelling and Capitalization

| | |
|---|---|
| SS | Are spelling errors located and corrected? |
| SS | Is spelling consistent throughout (*no switching between acceptable spellings*)? |
| SS | Is capitalization used appropriately (*proper nouns*, *etc*.)? |
| SS | Is capitalization of words consistent throughout the report? |

### Grammar and Punctuation

| | |
|---|---|
| MD | Are verb tenses used appropriately? |
| MD | Are marks of punctuation used appropriately? |
| MD | Is subject-verb agreement used in every sentence? |
| MD | Is the grammar checker updated and are underlined grammar issues addressed? |

### Writing Style

| | |
|---|---|
| DS | Are all sentences in the report easy for your audience to understand quickly? |
| SS | Are most sentences written in active voice? |
| SS | Are idioms and vague words eliminated from the report? |
| SS | Are acronyms introduced before being used? |
| MD | Are well-written topic sentences included at the beginning of each paragraph? |
| SS | Are lists parallel? |
| MD | Is the appropriate point of view used when addressing your audience or describing team actions? |