Model #101: Credit Card Default Model Performance Monitoring Plan

Tannia Dubon MSDS 498

1. The Production Model

The logistic regression model selected for production was developed using the glm() function and it was trained on a subset of variables. The variables themselves were selected using both the output from a Random Forest model that was trained on all the variables in the modeling suite and a logistic regression variable selection (regsubsets) method.

The logistic regression model was selected from the suite of models developed given that it is the most common method applied to scorecards (Thomas, 2009, p. 79) and its practical implementation and revalidation in a production environment with large data sets (Bhatti, 2018).

The use of the variable PAY_1, the only non-engineered variable included, will need to be addressed with the respective business unit given that the data that was received contained entries that were not listed in the data dictionary, and the use of the codes was inconsistent. It will be helpful to define the business rules for how the whole set of variables (PAY_1 – PAY_6) are used, to ensure that the variable imputations or adjustments are applied appropriately.

The precise code used to run this model was:

```
log_reg <- glm(DEFAULT ~ PAY_1 + Max_Util + Max_Pmt_Amt + Max_DLQ +
Bal_Growth_6mo_21390_428792 + Avg_Pmt_Amt_2833_12092 +AGE_25_32,
data=train_df, family=binomial)</pre>
```

The table of coefficients in Image 1 presents the significance levels of each of the variables and their estimated coefficient values.

```
Observations: 15180
Dependent Variable: DEFAULT
Type: Generalized linear model
Family: binomial
Link function: logit

MODEL FIT:

x²(14) = 2693.97, p = 0.00
Pseudo-R² (Cragg-Uhler) = 0.25
Pseudo-R² (McFadden) = 0.17
AIC = 13541.41, BIC = 13655.83
```

MODEL INFO:

| Standard errors. MLL | | | | |
|------------------------------|-------|--------|--------|------|
| | | | | |
| | Est. | S.E. | z val. | р |
| | | | | |
| (Intercept) | -1.48 | 0.04 | -34.29 | 0.00 |
| PAY_11 | 0.38 | 0.07 | 5.55 | 0.00 |
| PAY_12 | 1.76 | 0.08 | 21.91 | 0.00 |
| PAY_13 | 1.68 | 0.21 | 8.04 | 0.00 |
| PAY_14 | 1.61 | 0.41 | 3.94 | 0.00 |
| PAY_15 | -0.32 | 0.57 | -0.56 | 0.57 |
| PAY_16 | -0.13 | 0.78 | -0.17 | 0.86 |
| PAY_17 | 11.76 | 132.53 | 0.09 | 0.93 |
| PAY_18 | -0.47 | 0.88 | -0.54 | 0.59 |
| Max_Util | 0.21 | 0.05 | 4.04 | 0.00 |
| Max_Pmt_Amt | -0.00 | 0.00 | -5.34 | 0.00 |
| Max_DLQ | 0.30 | 0.02 | 15.74 | 0.00 |
| Bal_Growth_6mo_21390_4287921 | -0.26 | 0.13 | -1.97 | 0.05 |
| Avg_Pmt_Amt_2833_120921 | -0.39 | 0.05 | -7.86 | 0.00 |
| AGE_25_321 | -0.16 | 0.05 | -3.38 | 0.00 |
| | | | | |

Image 1: Table of Coefficients for Logistic Regression Model

All of the variables, with the exception of dummy variables PAY_15-18, have significance levels that would lead us to reject the null hypothesis, based on an alpha level of .05. The dummy variable PAY_17 has the largest coefficient. The value of the coefficient represents the average increase in DEFAULT for each unit of change when PAY_1 = 7, while holding all other predictor variables constant. This is a potential point of concern and requires close attention as it may result in a less robust model during re-validation. Table 1 below shows just how small the occurrence of PAY_1 = 5-8 really is.

| | Table 1: Pay_1 Values by Default | | | | | | | | | | | |
|---------|--|--|--|--|--|--|--|--|--|---|--|--|
| | -1 1 2 3 4 5 6 7 8 | | | | | | | | | | | |
| DEFAULT | DEFAULT 0 19975 2436 823 78 24 13 5 2 8 | | | | | | | | | 8 | | |
| | 1 3207 1252 1844 244 52 13 6 7 11 | | | | | | | | | | | |

2. Model Development Performance

This model performed relatively well on the training data. The Sensitivity indicates that the true positives for DEFAULT were correctly predicted 70% of the time. The Specificity reflects the rate at which the true negatives were predicted, that is 83% of the time.

| _ | | | | | | | | | | | | | |
|--------|---------------------------|----------|--------|--|--------|----------|----------|---------------|------|-----------|------|-------------|------|
| | Model Logistic Regression | | | | | | | | | | | | |
| | train data | | | | | | | | | | | | |
| Actual | Predicte | ed Class | Totals | | Actual | Predicte | ed Class | TP | 0.70 | TP+TN | 1.53 | AUC | 0.64 |
| Class | 0 | 1 | Totals | | Class | 0 | 1 | TN | 0.83 | Precision | 0.33 | Sensitivity | 0.70 |
| 0 | 11,284 | 2,300 | 13,584 | | 0 | 0.83 | 0.17 | Type I Error | 0.17 | Recall | 0.70 | Specificity | 0.83 |
| 1 | 473 | 1,123 | 1,596 | | 1 | 0.30 | 0.70 | Type II Error | 0.30 | F1 | 0.75 | | |

Image 2: Confusion Matrix for Training Data

The area under the curve (AUC) displays the tradeoffs between the Sensitivity and the Type I Errors for the model at different levels. The optimal area under the curve is 64%, a point on the curve at which Sensitivity equals .70 and the Type I Error equals .17.

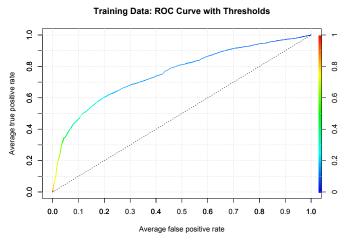


Image 2: ROC Curve for Training Data

Next, we consider the performance of the model on the testing data. The Sensitivity drops by 2%, so we can expect the true positives to be correctly predicted 68% of the time. The Specificity increases by 1%, so the true negatives are predicted at a slightly higher rate.

| | Model Logistic Regression | | | | | | | | | | | | |
|--------|---------------------------|----------|--------|--------|-------|---------|----------|---------------|------|-----------|------|-------------|------|
| | test data | | | | | | | | | | | | |
| Actual | Predicte | ed Class | Totals | Tatala | | Predict | ed Class | TP | 0.68 | TP+TN | 1.52 | AUC | 0.65 |
| Class | 0 | 1 | TOTALS | | Class | 0 | 1 | TN | 0.84 | Precision | 0.34 | Sensitivity | 0.68 |
| 0 | 5,512 | 1,028 | 6,540 | | 0 | 0.84 | 0.16 | Type I Error | 0.16 | Recall | 0.68 | Specificity | 0.84 |
| 1 | 254 | 529 | 783 | | 1 | 0.32 | 0.68 | Type II Error | 0.32 | F1 | 0.74 | | |

Image 3: Confusion Matrix for Testing Data

We don't see a dramatic increase or decrease in the AUC of the testing data. It increases by 1%, to 65%, given the increase in the Specificity to .84. The plot of the ROC curve reflects this in Image 5.

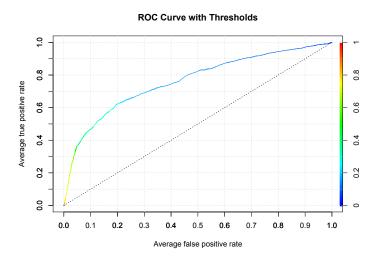


Image 3: ROC Curve for Testing Data

The Kolmogorov-Smirnov (KS) statistic scores the differences between the cumulative distribution functions using the densities of the binary response variable, by deciles or semi-deciles (Thomas, 2009, p. 111). The KS statistics for the training data are depicted in Table 2 below. The highest score of 40.2% represents the maximum difference between the cumulative distribution functions of the two groups and it takes place in the 6th semi-decile (the .70-.75 band). This score is expected to discriminate well (Thomas, 2009, p. 112), but it will need to be monitored as verification.

The 4^{th} , 5^{th} , 7^{th} , and 8^{th} semi-deciles were also close to the highest score, indicating that these are also areas of maximum distance and nearly have a good discrimination capacity.

| | Table 2. Kolmogorov-Smirnov Statistic Lift Chart for Training Data | | | | | | | | | | | |
|-----------------|--|-----------------|--------------------|-------------------|----------------------|---------------|------------------|------------|--|--|--|--|
| Semi- Decile | Obs | Target (Y=1) | NonTarget (Y=0) | Target Density | NonTarget Density | Target CDF | NonTarget CDF | KS Stat | | | | |
| 1 | 759 | 563 | 196 | 16.4% | 1.7% | 16.4% | 1.7% | 14.8% | | | | |
| 2 | 759 | 513 | 246 | 15.0% | 2.1% | 31.4% | 3.8% | 27.7% | | | | |
| 3 | 759 | 338 | 421 | 9.9% | 3.6% | 41.3% | 7.3% | 34.0% | | | | |
| 4 | 759 | 285 | 474 | 8.3% | 4.0% | 49.6% | 11.4% | 38.3% | | | | |
| 5 | 759 | 210 | 549 | 6.1% | 4.7% | 55.8% | 16.0% | 39.7% | | | | |
| 6 | 759 | 183 | 576 | 5.3% | 4.9% | 61.1% | 20.9% | 40.2% | | | | |
| 7 | 759 | 144 | 615 | 4.2% | 5.2% | 65.3% | 26.2% | 39.2% | | | | |
| 8 | 759 | 121 | 638 | 3.5% | 5.4% | 68.9% | 31.6% | 37.3% | | | | |
| 9 | 759 | 107 | 652 | 3.1% | 5.5% | 72.0% | 37.1% | 34.8% | | | | |
| 10 | 759 | 106 | 653 | 3.1% | 5.6% | 75.1% | 42.7% | 32.4% | | | | |
| 11 | 759 | 166 | 593 | 4.8% | 5.0% | 79.9% | 47.7% | 32.2% | | | | |
| 12 | 759 | 90 | 669 | 2.6% | 5.7% | 82.6% | 53.4% | 29.1% | | | | |
| 13 | 759 | 110 | 649 | 3.2% | 5.5% | 85.8% | 59.0% | 26.8% | | | | |
| 14 | 759 | 111 | 648 | 3.2% | 5.5% | 89.0% | 64.5% | 24.6% | | | | |
| 15 | 759 | 87 | 672 | 2.5% | 5.7% | 91.6% | 70.2% | 21.4% | | | | |
| 16 | 759 | 49 | 710 | 1.4% | 6.0% | 93.0% | 76.2% | 16.8% | | | | |
| 17 | 759 | 61 | 698 | 1.8% | 5.9% | 94.8% | 82.2% | 12.6% | | | | |
| 18 | 759 | 64 | 695 | 1.9% | 5.9% | 96.6% | 88.1% | 8.6% | | | | |
| 19 | 759 | 46 | 713 | 1.3% | 6.1% | 98.0% | 94.1% | 3.9% | | | | |
| 20 | 759 | 69 | 690 | 2.0% | 5.9% | 100.0% | 100.0% | 0.0% | | | | |
| Totals | 15,180 | 3423 | 11,757 | 100.0% | 100.0% | | | | | | | |

The KS scores were also calculated for the testing data. The highest score was 41.9% in the 6^{th} semi-decile; reflecting a 1.9% increase from the best score on the training data. Table 3 also shows that the 5^{th} and 7^{th} semi-deciles have good discrimination.

| | Table 3. Kolmogorov-Smirnov Statistic Lift Chart for Testing Data | | | | | | | | | | | |
|-----------------|---|-----------------|--------------------|-------------------|----------------------|---------------|------------------|------------|--|--|--|--|
| Semi- Decile | Obs | Target (Y=1) | NonTarget (Y=0) | Target Density | NonTarget Density | Target CDF | NonTarget CDF | KS Stat | | | | |
| 1 | 367 | 257 | 110 | 16.5% | 1.9% | 16.5% | 1.9% | 14.6% | | | | |
| 2 | 366 | 240 | 126 | 15.4% | 2.2% | 31.9% | 4.1% | 27.8% | | | | |
| 3 | 366 | 169 | 197 | 10.9% | 3.4% | 42.8% | 7.5% | 35.3% | | | | |
| 4 | 366 | 115 | 251 | 7.4% | 4.4% | 50.2% | 11.9% | 38.3% | | | | |
| 5 | 366 | 109 | 257 | 7.0% | 4.5% | 57.2% | 16.3% | 40.8% | | | | |
| 6 | 366 | 91 | 275 | 5.8% | 4.8% | 63.0% | 21.1% | 41.9% | | | | |
| 7 | 366 | 56 | 310 | 3.6% | 5.4% | 66.6% | 26.5% | 40.1% | | | | |
| 8 | 366 | 55 | 311 | 3.5% | 5.4% | 70.1% | 31.9% | 38.3% | | | | |
| 9 | 366 | 47 | 319 | 3.0% | 5.5% | 73.2% | 37.4% | 35.8% | | | | |
| 10 | 367 | 46 | 321 | 3.0% | 5.6% | 76.1% | 43.0% | 33.1% | | | | |
| 11 | 366 | 78 | 288 | 5.0% | 5.0% | 81.1% | 48.0% | 33.2% | | | | |
| 12 | 366 | 40 | 326 | 2.6% | 5.7% | 83.7% | 53.6% | 30.1% | | | | |
| 13 | 366 | 46 | 320 | 3.0% | 5.5% | 86.6% | 59.2% | 27.5% | | | | |
| 14 | 366 | 39 | 327 | 2.5% | 5.7% | 89.1% | 64.8% | 24.3% | | | | |
| 15 | 366 | 31 | 335 | 2.0% | 5.8% | 91.1% | 70.6% | 20.5% | | | | |
| 16 | 366 | 34 | 332 | 2.2% | 5.8% | 93.3% | 76.4% | 16.9% | | | | |
| 17 | 366 | 28 | 338 | 1.8% | 5.9% | 95.1% | 82.3% | 12.9% | | | | |
| 18 | 366 | 20 | 346 | 1.3% | 6.0% | 96.4% | 88.3% | 8.1% | | | | |
| 19 | 366 | 30 | 336 | 1.9% | 5.8% | 98.3% | 94.1% | 4.2% | | | | |
| 20 | 367 | 26 | 341 | 1.7% | 5.9% | 100.0% | 100.0% | 0.0% | | | | |
| Totals | 7,323 | 1,557 | 5,766 | 100.0% | 100.0% | | | | | | | |

3. Performance Monitoring Plan

In this section, the performance benchmarks listed below are based on a K-S statistic of 41.9% from the testing data. These thresholds along with routine re-validation procedures are necessary given that the critical area identified by the K-S statistic would not be valid in a scenario where the parameters for the distributions change.

| | Table 4. Performance Monitoring Rules | | | | | | | | | |
|---|---|---|--|--|--|--|--|--|--|--|
| Status K-S Statistic Threshold Definition | | | | | | | | | | |
| Red | 27 – 34 % The model needs redevelopment. | | | | | | | | | |
| Amber | 35 – 41 % | Model needs to be revalidated in 3 months | | | | | | | | |
| Green | Green 42 % Model is performing as expected. To be re-validated every 6 months | | | | | | | | | |

The corresponding confusion matrices benchmark the errors associated with the K-S statistic thresholds. These allow us to articulate what we expect to see in the different scenarios and to ensure alignment with risk thresholds.

| | Table 5. Confusion Mat | rices for Each Threshold Lev | /el |
|-----------------|------------------------------|------------------------------|---------------------|
| Conf | usion Matrix using K-S Scor | es for Testing Data with a 4 | 12% Cutoff |
| | | | |
| | Actual Goods | Actual Bads | Number so Predicted |
| Predicted Goods | 890 | 941 | 1,831 |
| Predicted Bads | 667 | 4,825 | 5,492 |
| Actual Numbers | 1,557 | 5,766 | 7,323 |
| Specificity | 0.571612075 | | |
| Type I Error | 0.428387925 | | |
| Sensitivity | 0.836801942 | | |
| Type II Error | 0.163198058 | | |
| Total Error | 0.22 | | |
| Confu | usion Matrix using K-S Score | es for Testing Data with a 3 | 5.8% Cutoff |
| | Actual Goods | Actual Bads | Number so Predicted |
| Predicted Goods | 1,092 | 1,837 | 2,929 |
| Predicted Bads | 465 | 3,929 | 4,394 |
| Actual Numbers | 1,557 | 5,766 | 7,323 |
| Specificity | 0.701348748 | | |
| Type I Error | 0.298651252 | | |
| Sensitivity | 0.681408255 | | |
| Type II Error | 0.318591745 | | |
| Total Error | 0.31 | | |

| Table 5. Confusion Matrices for Each Threshold Level | | | | | | | | | | |
|--|--------------|-------------|---------------------|--|--|--|--|--|--|--|
| Confusion Matrix using K-S Scores for Testing Data with a 27.5% Cutoff | | | | | | | | | | |
| | | | | | | | | | | |
| | Actual Goods | Actual Bads | Number so Predicted | | | | | | | |
| Predicted Goods | 1,303 | 3,091 | 4,394 | | | | | | | |
| Predicted Bads | 254 | 2,675 | 2,929 | | | | | | | |
| Actual Numbers | 1,557 | 5,766 | 7,323 | | | | | | | |
| | | | | | | | | | | |
| Specificity | 0.836865768 | | | | | | | | | |
| Type I Error | 0.163134232 | | | | | | | | | |
| Sensitivity | 0.463926465 | | | | | | | | | |
| Type II Error | 0.536073535 | | | | | | | | | |
| Total Error | 0.46 | | | | | | | | | |