# **MAT 303 Module Five Problem Set Report**

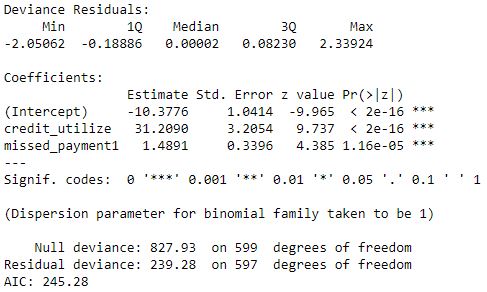
Logistic Regression

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This week I’m taking on the role of a risk analyst working for a credit card company. I have access to a set of historical data that can be used to study the relationships between customer characteristics and whether they are likely to default on their credit. This data is important because the credit company would like to calculate the risk of if their customers will default on their credit. There are many different important variables I will consider, such as the age of the individual, the sex, highest education level attained, marriage status, assets owned, missed payments in the last 3 months, and credit utilization. The entire set of data here contains 9 columns (variables) with 600 rows (samples). In this report I’ll be covering multiple different analyses. I’ll start with the generalized form of logistic regression and the linear form in terms of the natural log of odds along with a confusion matrix and report the counts for true positives, true negatives, false positives, and false negatives while also reporting the accuracy, precision, and recall of that matrix. After that, I’ll perform a Hosmer-Lemeshow goodness of fit test to assess whether the model is a good fit for the data set. After that, I’ll be performing a Wald’s test on the beta estimates to see if they’re a good fit for the model as well. Afterwards, I’ll be creating an ROC curve graph and interpreting the value of the AUC. Lastly, in addition to everything else, I want to create a new data frame that I can use to visually show a graph that has the index of samples compared to the probability of defaulting.

 For this first part, the general form of a logistic regression model that I’ll use here for defaulting on credit, using credit utilization and missed payment as independent variables is . In the linear form using the natural log of odds, I would express the beta terms as =+. In this linear form, the term is representing the probability of success while the represents the probability of failure. Using this together, is the probability of success divided by the probability of failure. Putting “ln” in from of it lets me get the logit of probability or otherwise known as, the log odds. Creating my regression model, I will write it in terms of E(y) and in terms of the natural log of odds. These two formulas would be and respectively. Getting the summary printout for this allows up to do a lot more with the information.

This summary has a lot to tell. To start off, the deviance residuals are looking good because they are around 0 and somewhat symmetrical. The first beta estimate, the intercept, is -10.3776. This is the log odds an individual will default on their credit with no other parameters. The other two beta estimates of credit utilization (31.2090) and missed payments (1.4891) are the log odds ratio of the odds that a person will default on their credit over the odds that they would without them implemented. Since the second beta estimate is a percentage based on the utilization of credit, I can express this in terms of odds and not log odds. To do this I would divide the number by 100 for the percentage and get 0.312090 and then add that as a power to Euler’s Number and minus one from it () and get 0.36627. Now, this value must be multiplied by 100 to get its percentage which would equal 36.627%. Since it’s a positive number, the odds of defaulting will increase by 36.627% for each percentage increase in credit utilization if I hold all other variables constant. The null deviance and residual deviance in this model can also be used for different calculations. I want to use them to calculate the and overall P-value of the model here. To get the overall P-value of the model, I would take the null deviance minus the residual deviance to get and considering there are 2 predictor variables (so 2 predictor variables degrees of freedom), using a chi-square score to p-value calculator I would get an overall P-value of 0. To calculate the McFadden’s value, I will use for a value of 0.71099. This is a moderately high positive value and considering the P-value extremely under 0.05, the model itself is very good. Let’s look now at the A picture containing text

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Looking at this matrix, there are 246 true negatives, 29 false positives, 295 true positives, and 30 false positives. Using this information, I want to calculate the accuracy, precision, and recall. What these calculate are how many time the model was correct overall (accuracy), how good the model is at predicting a specific category (precision), and how many times the model was able to detect a specific category (recall). These three values are calculated like this: , , and . Putting my values of TP(true positive), TN(true negative), TN(true negative), and FN(false negative), I get values for accuracy at 90.166%, precision at 90.769%, and recall at 91.049%.

Above is the Hosmer-Lemeshow goodness of fit test. The P-value here is 0.4298, which is well above the 0.05 value and a low chi squared value, I would reject the alternative hypothesis of the model does not fit the data for the null hypothesis of the model fits the data. Looking further at this and making a Receiver Operating Characteristic curve graph, this is how it would look:

Chart

Description automatically generated This is the shape of this ROC graph. What it illustrates is the diagnostic ability of the binary classifier default. Since the classifiers give curves closer to the top-left corner, it indicates a better performance. As a baseline, a random classifier is expected to give points lying along the diagonal, so the farther away from the 40-degree diagonal of the ROC space, the more accurate the test. In this test, my AUC (area under the curve) is 0.9859. This number measures the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve. The higher the AUC, the better the performance of the model is at distinguishing between the positive and negative classes.

Using this model to predict the probability of an individual who has a credit utilization of 32% and has missed payments in the past three months defaulting on credit would be calculated by using . The resulting probability would be 0.75, or a 75% chance. If we ran the same data but put in for the individual not missing a payment in the last three months the probability of defaulting drops to 0.6331, or 63.31%. To convert these numbers into odds, I’ll divide the probability by one minus that probability. For the 0.75 result of having 32% credit utilization and missing a payment in the past three months, the odds become 3:4. When not missing a payment in the past three months is factored, the odds become 6331:3669.

In this next model, I’ll be using three predictor variables instead of two. Here, the variables used to predict the probability of defaulting on credit are credit utilization, assets, and education. The education variable in there will be either “1” for high school education, “2” for undergraduate education, and “3” for post graduate education. The assets variable will be “0” for no assets, “1” for car as only asset, “2” for house as only asset, and “3” for both car and house as asset. This formula is written in general logistic regression form as and in in the natural log of adds form as . To get my specific model, I will run a summary to get the intercept and beta estimates.

### Table Description automatically generatedA screenshot of a computer Description automatically generated with low confidenceLooking at this printout, my model for the general logistic form becomes and in the linear natural log of odds form as .

On this next confusion matrix, the number of true positives is 311, false positives are 10, true negatives are 266 and false negatives are 13. I’ll use the same formula as before to find the accuracy, precision, and recall here. Accuracy comes out to 0.9616 (96.16%), precision comes to 0.9688 (96.88%), and recall comes to 0.9599 (95.99%).

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generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAYABgAAD/4RD6RXhpZgAATU0AKgAAAAgABAE7AAIAAAAQAAAISodpAAQAAAABAAAIWpydAAEAAAAgAAAQ0uocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAEJlbmphbWluIExlYW5uYQAABZADAAIAAAAUAAAQqJAEAAIAAAAUAAAQvJKRAAIAAAADOTYAAJKSAAIAAAADOTYAAOocAAcAAAgMAAAInAAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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Again, looking at this model, the deviance residuals are fairly symmetrical and are around 0, so that looks good. Getting the overall and P-value here, I’ll judge this model based on a 5% level of significance. The value is 0.85042 and is showing a strong positive result. The P-value ends up being less than 0.00001 leaving it well below the 0.05 level I was looking for; making this model significant.

Looking at the Hosmer-Lemeshow goodness of fit test here, having such a low chi squared number and a 1 for the P-value, the model fits the data very well. I would reject the negative hypothesis of for the null hypothesis of

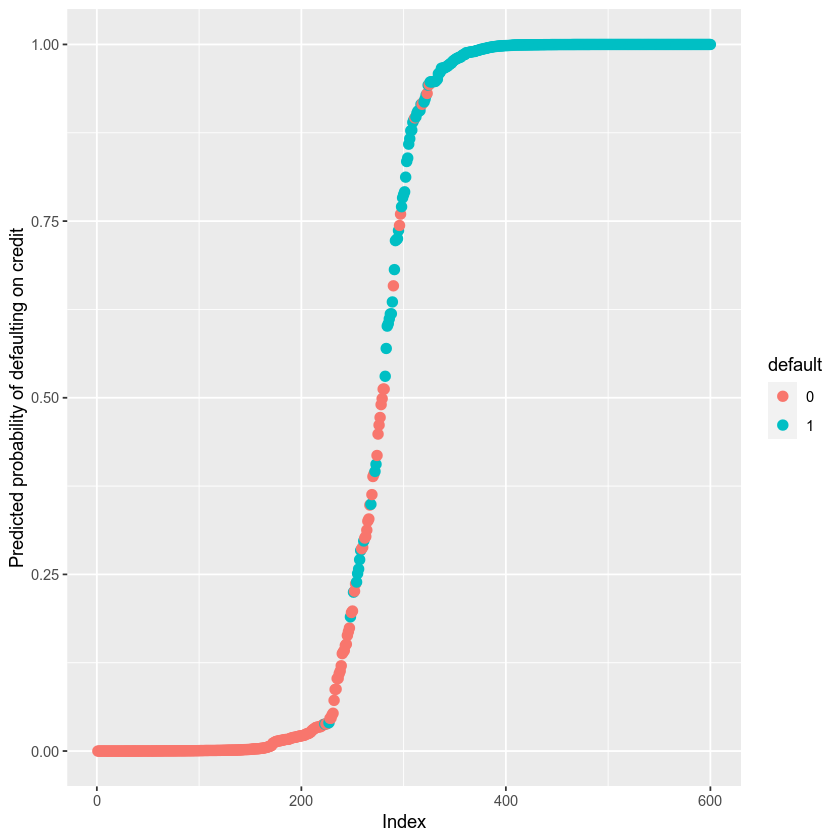
Chart

Description automatically generated Looking through the model itself, all the terms are significant at the 5% level except one, assets “0”. This is saying that just the individual with no asset’s variable is not relevant. If I were to rebuild this model, I would remove the zero assets variable from this data set.

The ROC graph for this model is an improvement on the last. While the other one was quite good as well, this one has an AUC (area under curve) of 0.9936 making it stellar. This model is quite certain that the estimation of probability is going to be correct.

Using this new model, I will predict the probability of an individual who has a credit utilization of 43%, owns a car and a house, and has attained a high school education defaulting on credit as well as an individual with the same variables expect has a postgraduate education. Using my model from before, I will plug in the numbers to calculate the probability. The model comes out to look like this: . The results of the individual with just a high school education, a car and a house, and 43% credit utilization comes out to a 0.984 (98.4%) chance of defaulting on credit. Changing the values now to show for a person with a postgraduate degree, the probability of defaulting drops to 0.3468 (34.68%). The odds for both would be 123:2 on the first case, and 867:1633 on the second case. As you can see, the odds and probability of defaulting are greatly impacted by the level of education an individual has.

For this last part, I wanted to show a graphical representation of this data (from the second model) to show a visual to get a better understanding. In the picture is has the index or people ranked in order of probability from low to high with red meaning the individual did not default, and green being that the individual did default.

 In conclusion, based off all the analyses I’ve ran, I would definitely recommend this model assuming that the sample size is sufficiently large (which it is at 600). The results from each test have shown, based off shape, P-value, and values, these models are good for predicting the risk of an individual defaulting on credit or not. These types of models have great practical importance as financial institutions all over the world need to know the risk, how to calculate the risk, and implement a system of borrowing where they make good decisions.

## **6. Citations**

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