Risk Benefit Analysis for Toast-USB Launch

Alli McCarty, Nick Mobley, Nijia Ke

3/18/2021

Abstract:

The popularity of toast as an American breakfast food as well as recent trends in technology have created a potential marketspace for the Toast-USB, which allows individuals to curate gourmet toast straight from their computer. We performed a risk-benefit analysis on two samples obtained from Toast Co.'s Department of Experiments (DOE) to investigate the potential favorable response rate for the product as well as potential target demographic groups for the marketing campaign. A series of logistic models were built to investigate the potential success of this product. We found that the best logistic model included demographic variables representing loan, age, default, and education as demographic indicators of interest. However, the favorable response rate for the product was 12.14%, which was roughly half of the necessary response rate required for launch of the product. Thus, based on this risk-benefit analysis, we do not recommend that Toast-Co move forward with this campaign. However, we do have some actionable next-step suggestions for Toast-Co to implement to continue their exploration in this exciting market space.

Introduction:

Toast has been a staple in the American breakfast for many decades. Avocado and hummus toast has also been the center of Millennial and Gen-Z dietary trends, creating a surge in the popularity of gourmet toast. The sustained popularity of toast as a breakfast food coupled with a recent drive in demand for gourmet toast created a potentially high-potential market space to combine toast with technology. Our client, Toast Co., is aiming to capitalize on a first-mover advantage and explore this new potential market space. Thus, Toast Co., has created the Toast-USB which enables individuals to curate gourmet, artisanal toast right from their computer.

Our aim is to assist Toast Co. to make informed, data-driven decisions regarding the launch of Toast-USB. Toast Co. conducted a first round market analysis from five metropolitan areas (including Toronto, ON; New York City, NY, Philadelphia, PA; Dallas, TX, and San Francisco, CA). Preliminary results were so promising that our firm's DOE has conducted another larger-scale study to determine the likelihood of success of Toast-USB. During the course of this investigation, we will synthesize the key findings from the first and second study. This includes significant data processing to both reconcile the data of the first and second study, as well as to process demographic data such that it can be used in model analysis. Further exploratory analysis will be performed to investigate key demographic groups that are significant predictors of a favorable response rate. To perform a risk-benefit analysis on continuation of the campaign, we will build a series of logistic models using demographic predictors of interest, and use cross validation based on maximizing the likelihood ratio to select the model. The model selection should provide insight on which demographic groups should be targeted by the marketing campaign, should Toast Co. move forward with the launch. Next, we will predict the favorable response rate based on the selected model, and give a binary(Y/N) recommendation on launch of the product. Finally, we will determing an MSRP for the product using a simulation of the logistic model.

The Data

The original dataset obtained from Toast Co.'s market analysis contained 421 observations of 8 variables, including 6 categorical variables and 2 numeric variables. The data used for supplementary analysis was provided by our firm's DOE where additional respondents were sampled from the same 5 major metropolitan areas to supplement the initial campaign, which gathered information on 45,211 observations for 16 different variables, including 9 categorical variables and 7 numeric variables. Variables relating to the demographic information of the respondents were all self reported, while variables pertaining to duration of contact and number of contacts were recorded by campaign administers. Description of all variables can be found in the data dictionary of the appendix.

Examining Missing Data

From the given data there are 45,211 observations. However there are 17,216 (38.10%) observations that contain one or more missing values. Certain categorical variables had missing values with no clear pattern of missingness. These variables included job, education, contact, previous days from contact, personal loan status, default status, marital status, and education. With these variables we decided to add another category termed "Unknown" to represent observations where the respondents elected to either not respond or were unable to provide adequate information. However we still needed to address observations that had missing values in the continuous variables.

We first wanted to understand if the continuous variables were missing in any distinct pattern. From Figure 1, it appears that the data is missing at random. In Figure 1, the red cells represent variables that are missing for a specific pattern, while the numbers on the left represent how many instances that pattern appeared in the data set. The number at the bottom of the graphic represents the total number of times the variable of the column was missing. The graphic suggests that we only observed 3 rows in which the pattern had 3 missing variables at once. These three patterns only appeared 13 times in our data set. The infrequency of these patterns signify that these patterns did occur randomly. Furthermore, there were 6 distinct patterns that were missing 2 or more variables with a total of 439 occurrences. Since all the patterns of missing data occurred with a low frequency, it is assumed that all of our missing values are missing at random. This reinforces that the quality of sampling and surveying conducted by the DOE, as well as gives us the freedom to either delete or impute the missing values without the worry of skewing the data inappropriately.

```
##       day pdays previous balance campaign  age duration
## 37712   1     1        1       1        1    1        1    0
## 2818    1     1        1       1        1    1        0    1
## 2278    1     1        1       1        1    0        1    1
## 161     1     1        1       1        1    0        0    2
## 1272    1     1        1       1        0    1        1    1
## 89      1     1        1       1        0    1        0    2
## 77      1     1        1       1        0    0        1    2
## 9       1     1        1       1        0    0        0    3
## 679     1     1        1       0        1    1        1    1
## 46      1     1        1       0        1    1        0    2
## 41      1     1        1       0        1    0        1    2
## 25      1     1        1       0        0    1        1    2
## 2       1     1        1       0        0    1        0    3
## 2       1     1        1       0        0    0        1    3
##         0     0        0     795     1476 2568     3125 7964
```

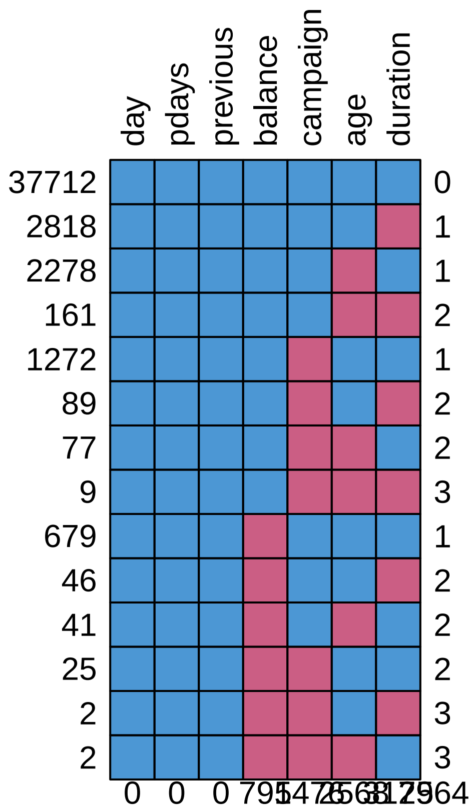


Figure 1: Missingness pattern of continuous variables in the second study

Imputing Continous Variables

After determining that the four variables containing missing values (balance, campaign, age, and duration) were all missing at random, we decided to address this issue by performing a single imputation of the median to replace the missing values. We conducted an imputation, as opposed to deleting all observations with missing data in an attempt to preserve the information of the other 15 variables in these 7,964 observations.

We determined that the median, as opposed to the mean, was the appropriate measurement to impute the values since all the variables of interest except age where all right-skewed. Because the variables were skewed, replacing the missing values with the mean would have drastically shifted the imputed data sets distributions farther to the right than expected. This median is not susceptible to skewness meaning the new imputed distributions will be representative of the original data set.

Specific Aims 1: To compare the demographic features of the sample from the first study to that of the second study qualitatively and quantitatively.

Graphic Comparison for the First and Second Sample

We first compare the demographic features common in both studies, including two numeric variables age and non-mortgage loan balance, as well as five categorical variables job, education, marital status, mortgage and primary phone.

To determine whether the decision to purchase the product is statistically associated with the numeric variable age in the second study, we generated a boxplot to compare the age distribution of respondents who are willing to purchase the product against those who are not. As is shown in Figure 2, people who are willing to purchase the product have a slightly wider range of age than those who aren't, but overall, the means of two populations appear to be only slightly different. However, based on the Welch Two sample t-test, we verified that the means are significantly different.

To compare the results with the first study, we further obtained the 95% confidence intervals for the age of people in two populations as delineated by whether they are willing to purchase the product. We are 95% confident that respondents who agree to purchase the product are from 23 to 74 years old, and those who refuse to purchase the product are from 25 to 60 years old. As provided in the first study, the mean age of individuals who agree to purchase the product is 25.5, falling fairly close to the lower bound of the 95% confidence interval in the second study, so it's likely that people who are willing to buy the products from the two studies are not representing the same population. However, the mean age of respondents who refused to buy the product is 37.5, which is close to the mean age of the counterpart in the second study (39 years old). Overall, we believe that based on age, samples in the two studies are unlikely from the same population.

Next, to determine whether the choice to purchase the product is statistically associated with another numeric variable non-mortgage loan balance in the second study, we generated a density plot to compare the age distribution of respondents who are willing to purchase the product against those who are not, as is shown in Figure 3. The graph indicates that both distributions are right skewed, and they overlap to a great proportion with the distribution of respondents who refuse to buy the product being slightly less right skewed. It can be inferred that respondents who refused to buy the product might have a lightly lower balance on average, and as verified by Welch Two sample t-test, the true means of two populations are significantly different.

We also obtained the 95% confidence intervals for the non-mortgage loan balance of people in two populations as delineated by whether they are willing to purchase the product. We are 95% confident that in the second study, respondents who agree to purchase the product have non-mortgage loan balance between -157.45 and 10185 dollars, and those who refuse to purchase the product have non-mortgage loan balance between -393 and 8266 dollars. Similar to the varible age, the average non-mortgage loan balance of individuals who refuse to purchase the product ($1250) in the first study falls within the 95% confidence interval of its counterpart in the second study. However, the average non-mortgage loan balance of individuals who agree to purchase

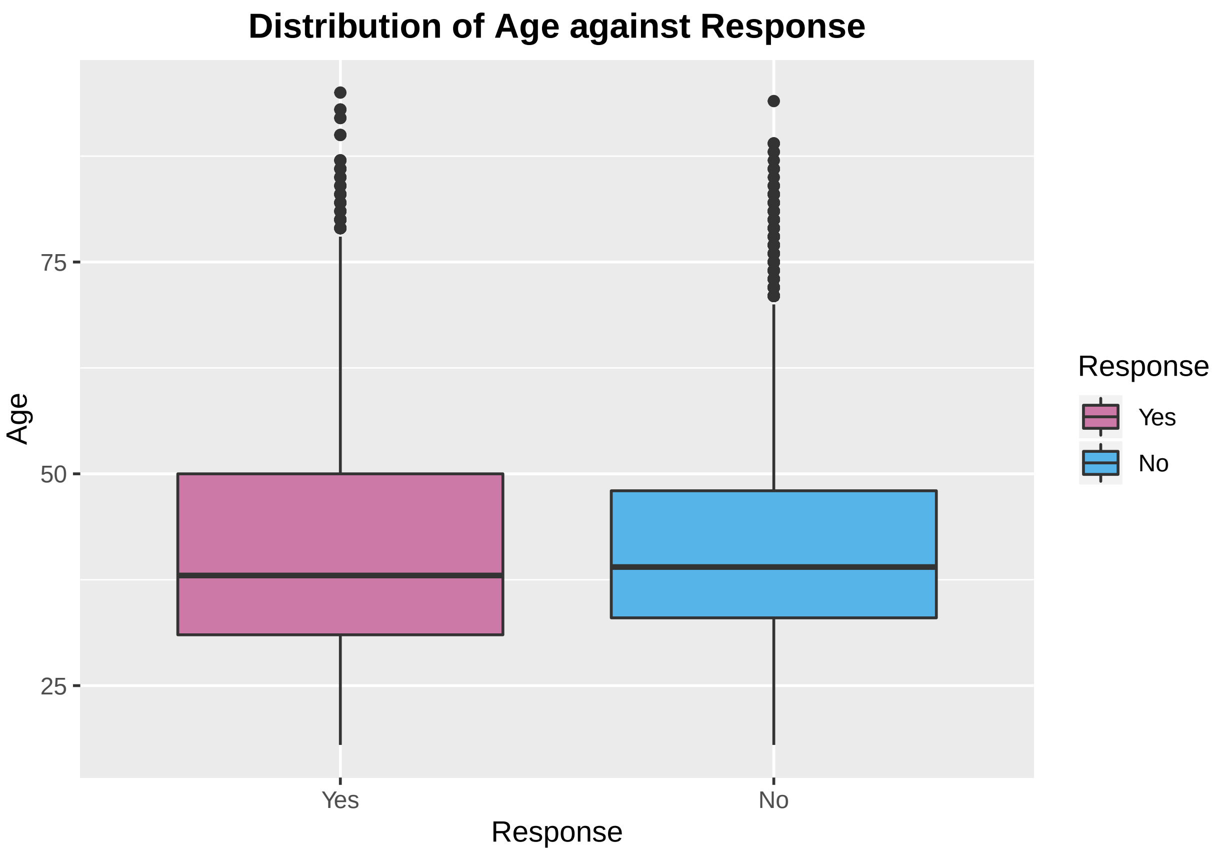


Figure 2: Age distribution of respondents against response in the second study

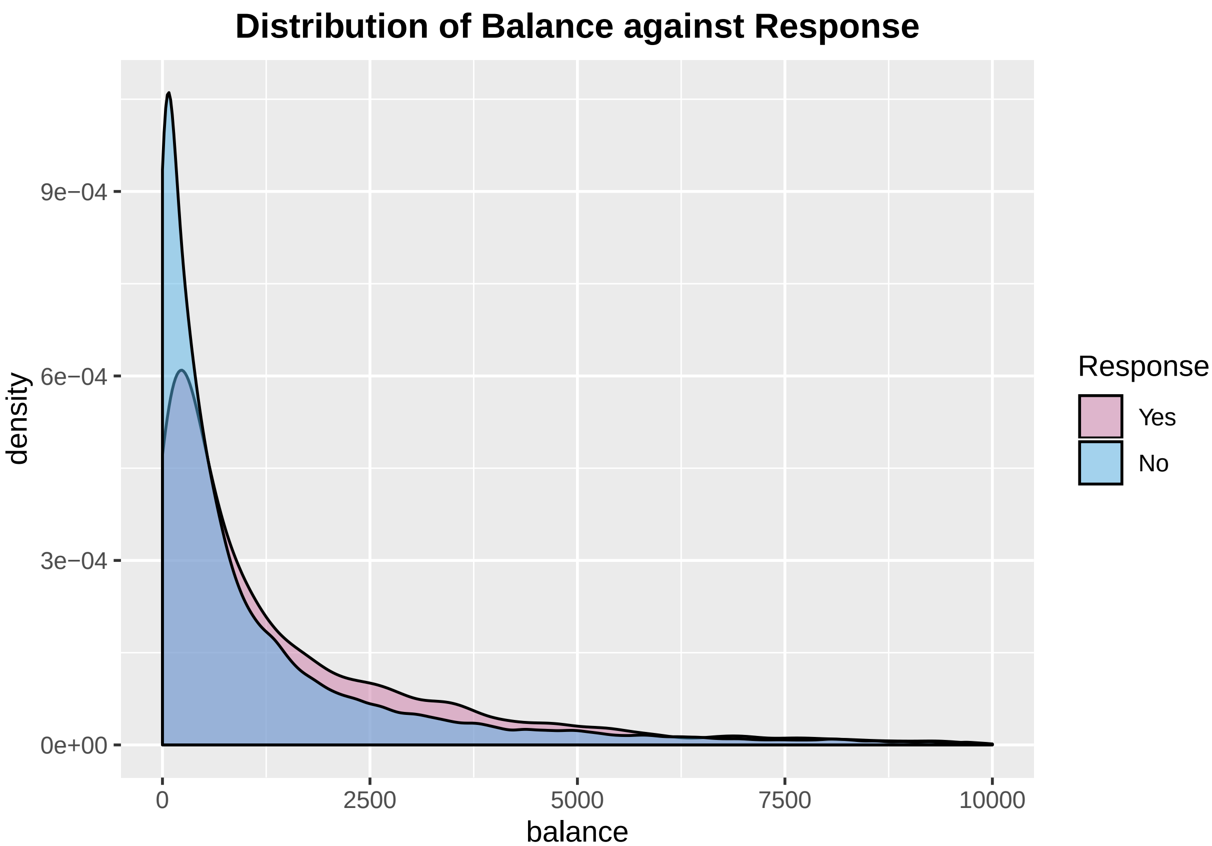


Figure 3: Distribution of non-mortgage loan balance against response in the second study

the product is 23879 dollars, being way higher than the upper limit of its counterpart in the second study, the sample in the first study is unlikely from the same population of the second study.

Next, that, we continued to compare the categorical varible job in both studies. Figure 4 shows the number of respondents of each type of job in the second study as delineated by their responses to buy the product, which is ranked by the order of counts in the refusal group from high to low. Regardless of the reponse, it appears that most of the respondents are blue-collar, technician or involved in management, but students and households only take up a fairly small proportion of the sample.

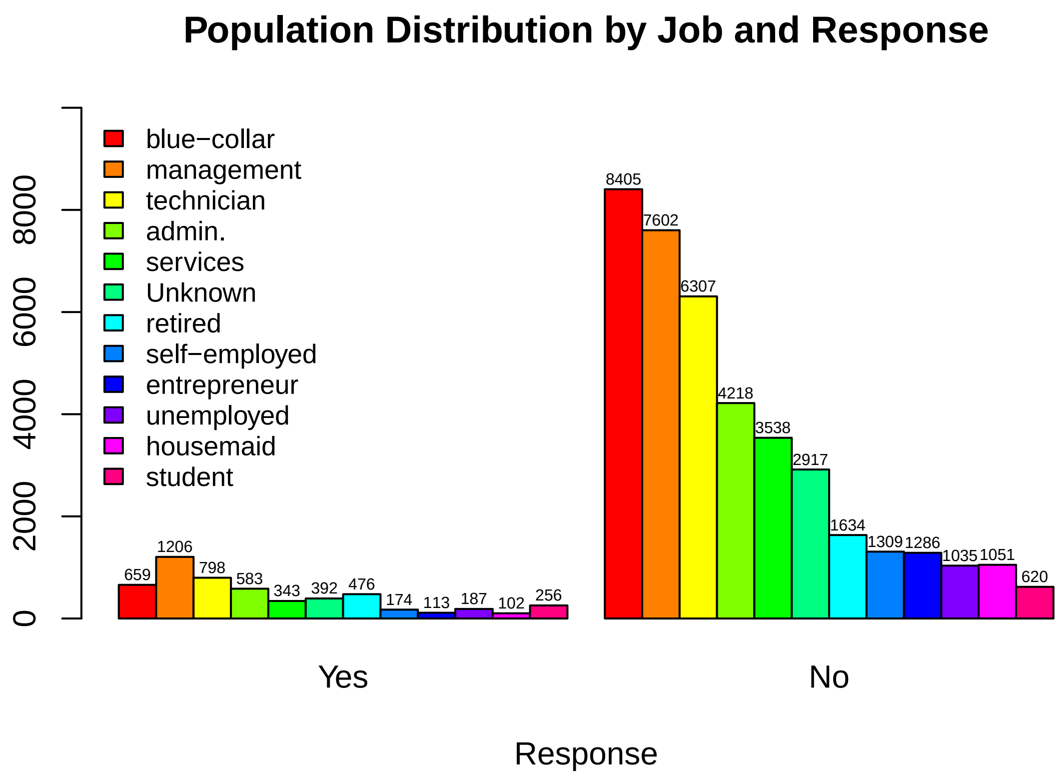


Figure 4: Population distribution of respondents by job and response in the second study

In order to allow for the comparison of job distributions in the two studies, we collapsed blue-collar and technician into one category, counted respondents who are entrepreneurs, administrators or involved in management as white-collar and combined unemployed and unknown into one category. Households and students are directly considered as single levels of the job factor. With all the remaining job types omitted, we generated barplots in Figure 5 to compare the distributions against response. In stark contrast to what we observed for the second study, in the first study, the most common job is student, whereas blue collars are hardly seen. This clearly indicates that according to job type, the two studies are not based on the same population.

We also compared the distribution of respondents with different education backgrounds as delineated by their response to purchase the product, as is shown in Figure 5. The tertiary education in the second study can be regarded as the the same as the college and more level in the first study, so the relevant bars were all highlighted in red. From the figures, we can see that although there're similar numbers of respondents who agree or refuse to buy the product in the first study, in the second study there're apparently more respondents who refuse to buy the products than agree. The majority of the respondents involved in the first study has education level of college or higher, whereas in the second study , there's less respondents

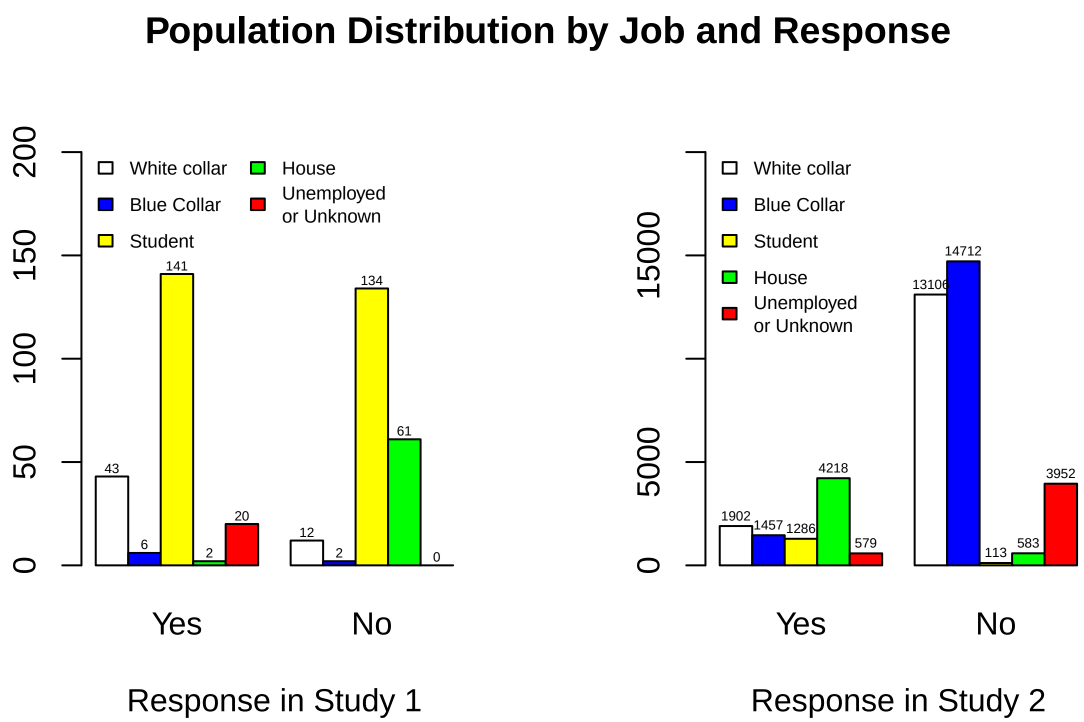


Figure 5: Population distribution of respondents by job and response in both studies

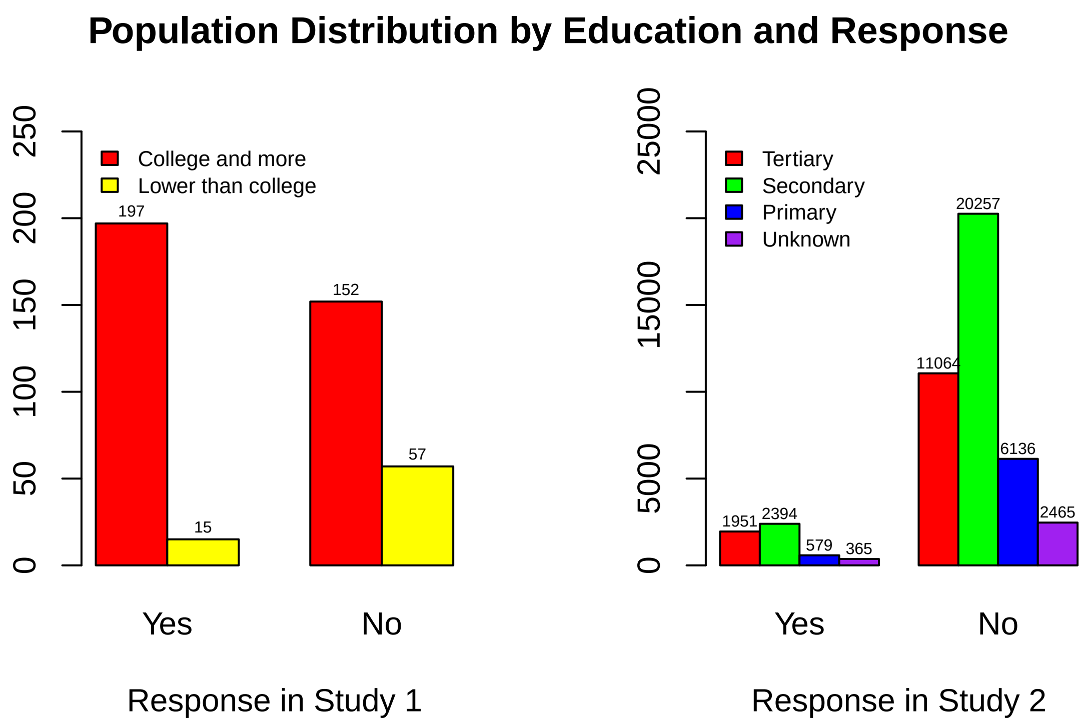


Figure 6: Population distribution of respondents by education and response in both studies

with college education than respondents with secondary education. It seems that based on education levels, these two studies are not from the same population.

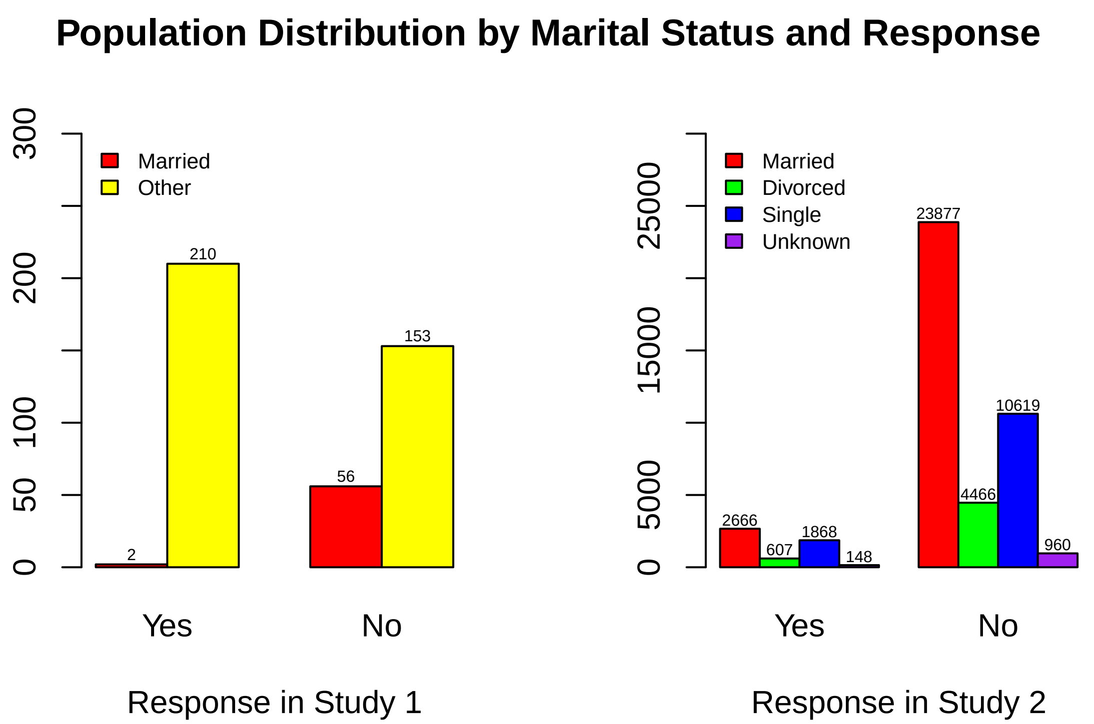


Figure 7: Population distribution of respondents by marital status and response in both studies

Similarly, We also compared the distribution of respondents with different marital status against their response to purchase the product, as is shown in Figure 6. In the first study, there're significantly lower numbers of married respondents than not married respondents, whereas there're about equal total numbers of married respondents as those not married. Therefore, these two samples are unlikely from the same population. Interestingly, if we focus on the distribution of married respondents in both studies, we can see that in both study, married respondents are unlikely to purchase the product.

Furthermore, we compared the distribution of respondents with or without mortgage against their response to purchase the product, as is shown in Figure 7. Similar to what we observed in Figure 6, in the first study, the majority of the respondents are without mortgage, whereas in the second study there are about comparable number of respondents who have mortgage or not. This could serve as edividence to show that the second study was well designed to randomize the sample. To our notice, in both studies, people with mortgage are less likely to purchase the product as compared to those with no mortgage. This could be explained as if people with mortgage are more prudent with how they should spend money. However, we see conflicting trends of response in the two studies among the group with no mortgage, which could result from the difference in sampling.

With regard to the distribution of respondents use cell phone or not as their primary phone against their response to purchase the product (shown in Figure 8), it appears that less than half ot the respondents use cell phone as their primary phone in the first study, whereas more than half of the respondents use cell phone as their primary phone in the second study. The second study may be representing the usual cases, as nowadays people tend to use cell phone more often than before. Interestingly, although respondents who use

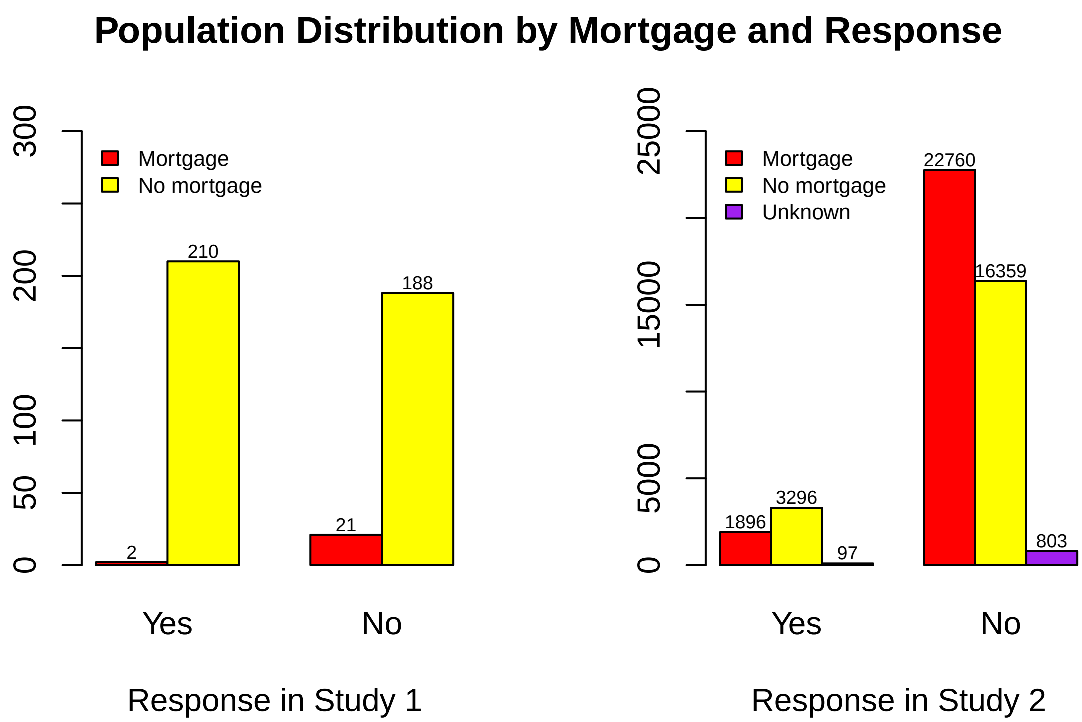


Figure 8: Population distribution of respondents by mortgage and response in both studies

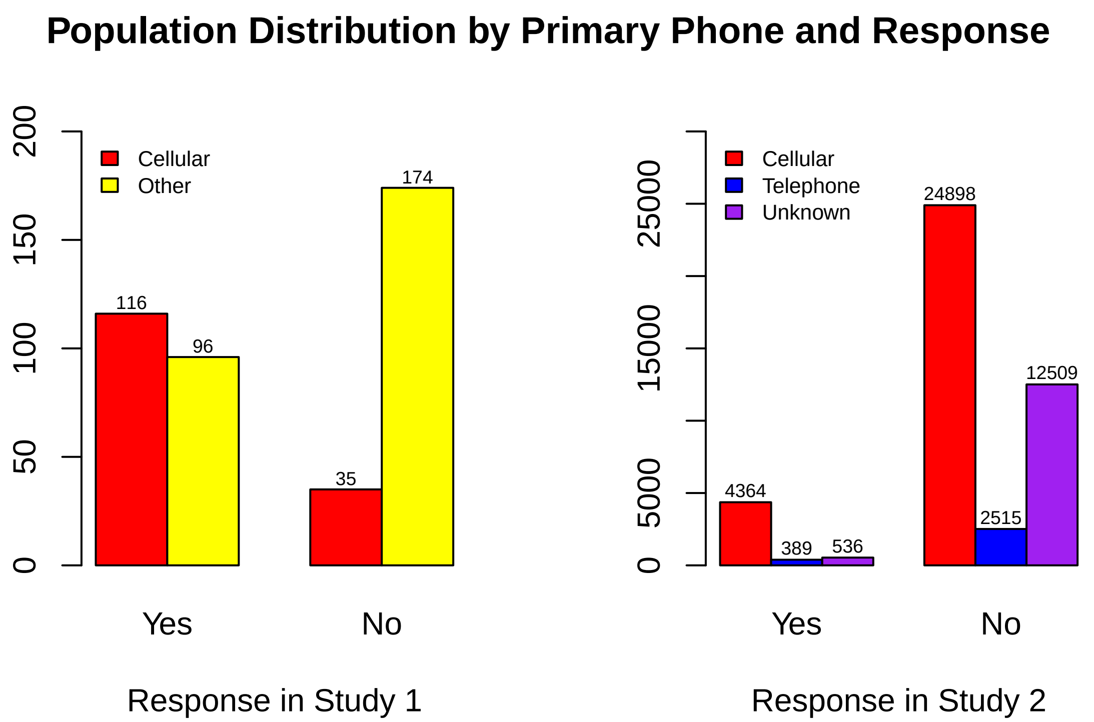


Figure 9: Population distribution of respondents by primary phone and response in both studies

cell phones as their primary phone tend to agree to buy the product in the first study, this trend is reversed in the second study, with the majority of the respondents refused to buy the product. Apparently, these two samples are not from the same population.

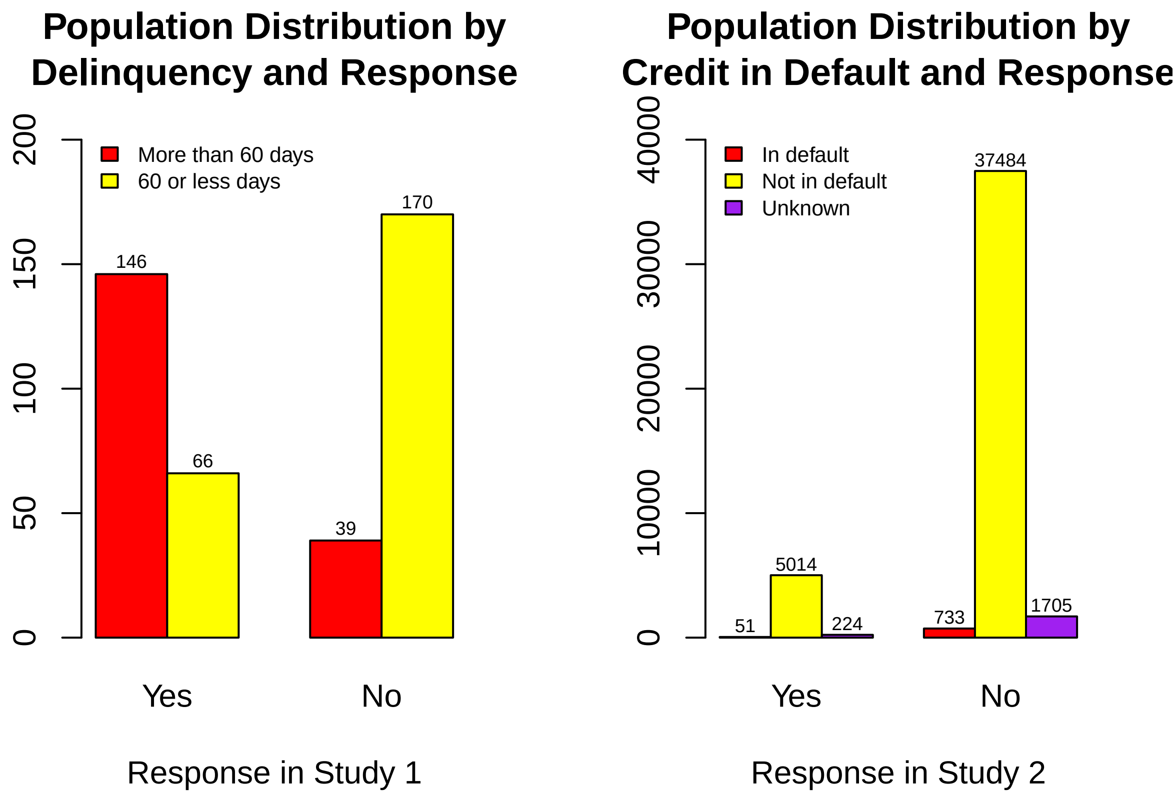


Figure 10: Comparison of the population distribution by delinquency and response in the first study against the population distribution by credit in default and response in the second study

It's possible that people in delinquency for more than 60 days also have credit in default, so we compared the delinquency variable in study one with the credit in default varible in study 2, as is shown in Figure 9. To our notice, the great majority of the respondents in the second study are do not have credit in default, whereas in the first study respondents that have less than 60 days of delinquency account for only slightly more than half of the whole sample. Interestingly, in the first studies, respondents that has less than 60 days of delinquency are less likely to buy the products, and a similar trend is observed in the second study, where the majority of repondents with no credit in default refuse to buy the product.

Now that the variables common in both studies have been scrutinized, we continued to examine the pattern of distributions with variables only described in the first study, including gender and race. Figure 10 displays the side-by-side distribution of respondents of different gender or race against response. It appears that male and white people both take up the majority of the respondents, which could potentially lead to biased response rates.

In the second study, whether or not a respondent has personal loan is the only variable reflecing demographic features that haven't been looked into. Consistent with what we observed for the credit in default variable, the majority of the respondents are with no personal loan. Interestingly, regardless of having personal loan or not, they both tend to not buy the product, with similar probabilities.

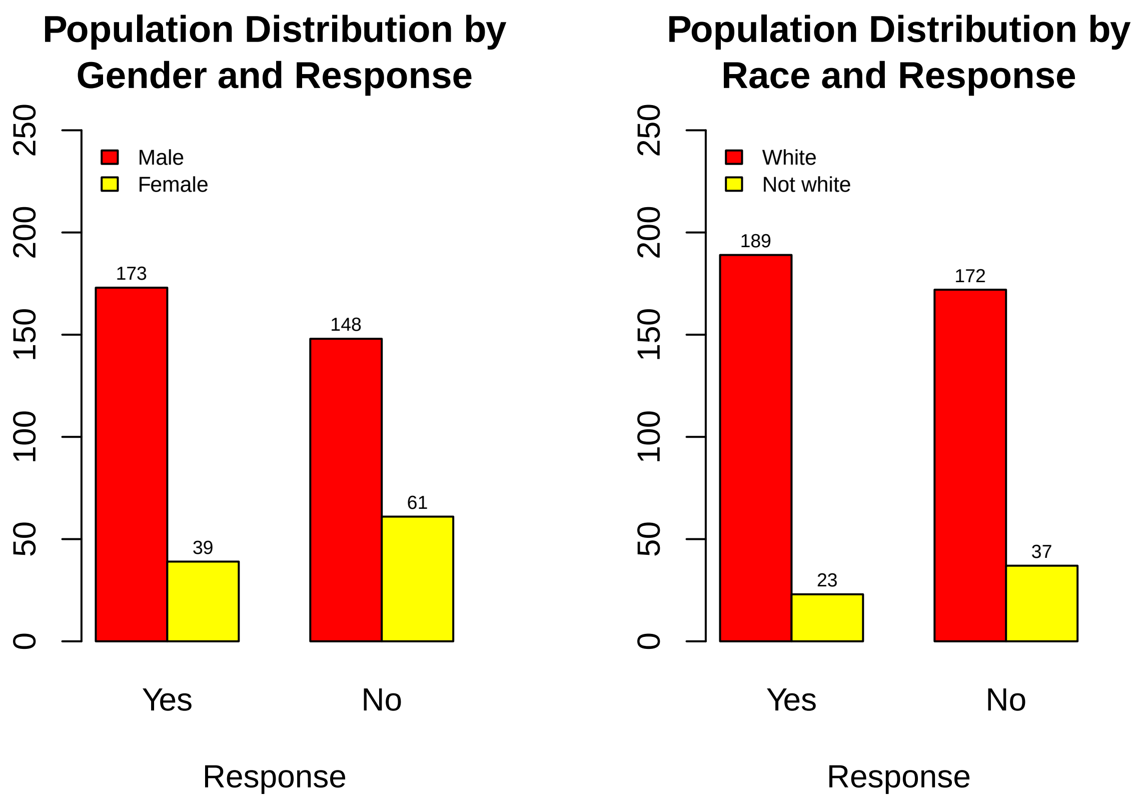


Figure 11: Population distribution of respondents by gender against response or by race against response in the first study

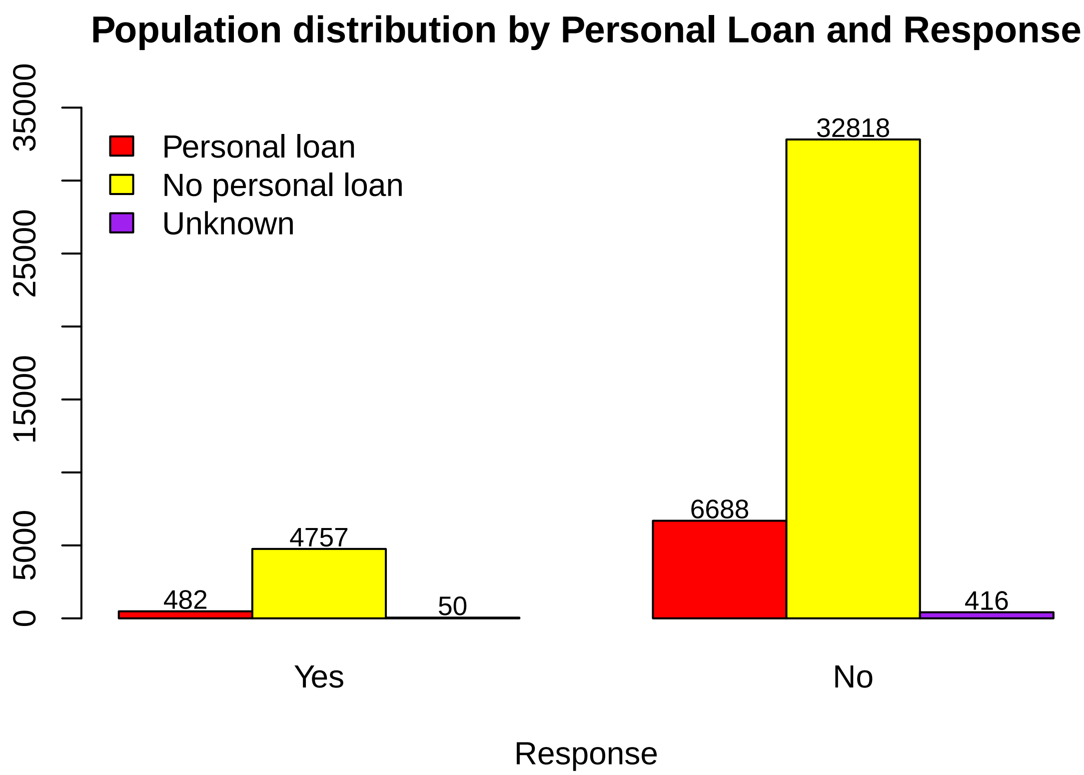


Figure 12: Population distribution of respondents by personal loan and response in the second study

Likelihood ratio tests

Next, we conducted likelihood ratio tests to examine whether response to purchase the product is dependent on each categorical variable reflecting demographic features. For the first study, likelihood ratio test statistics, degrees of freedom and p-values of the tests on the eight variables (job, education, marital status, mortgage, primary phone, delinquency, gender and race) has been shown in Table 1, with all of the p-values being less than 0.05, indicating that there is significant evidence that response to buy the product are associated with each of these eight variables.

Variable	Levels	G2	df	P-value
Job	White Collar, Blue Collar, Student, House, Unemployed or Unknown	321.67	4	< 0.001
Education	College and more, Lower than college	31.92	1	< 0.001
Marital	Married, Not married	71.97	1	< 0.001
Mortgage	Mortgage, No Mortgage	19.49	1	<0.001
Primary Phone	Cellular, Other	68.66	1	<0.001
Delinquency	More than 60 days, 60 or less days	113.33	1	<0.001
Gender	Male, Female	6.81	1	0.009
Race	White, Not White	4.08	1	0.043

Table 1: Likelihood ratio tests of the dependence of response on the demographic variables in the first study

Similarly, Table 2 reflects the likelihood ratio tests of whether response to purchase the product is dependent on each of the demographic categorical variable in the second study, including job, education, marital status, mortgage, primary phone, credit in default and personal loan. The categories used are based on the original levels of factors in the second study. the Similar to what we observed in Table 1, all of the p-values are less than 0.05, suggesting that there're significant evidence that response to buy the product are dependent on each of these seven variables.

Variable	Levels	G2	df	P-value
Job	Administer, Management, Entrepreneur, Blue-collar, Technician, Student, Housemaid, Unemployed, Unknown, Self-employeed, Services, Retired	698.03	11	< 0.001
Education	Tertiary, Secondary, Primary, Unknown	226.34	3	< 0.001
Marital	Married, Single, Divorced	193.16	2	< 0.001
Mortgage	Mortgage, No Mortgage	868.71	1	<0.001
Primary Phone	Cellular, Telephone, Unknown	68.66	1	<0.001
Credit in default	Credit in default, No credit in default	24.33	1	<0.001
Personal Loan	Personal Loan, No personal loan	232.1	1	<0.001

Table 2: Likelihood ratio tests of the dependence of response on the demographic variables in the second study

Since for response is statistically associated with each of the five categorical variables common in both studies, we further conducted five more likelihood ratio tests to examine whether the samples in the two studies are from the same population. Assuming that they are two samples from the same population, then the proportion of each level of the interaction terms of response and any of the five categorical variables should be the same for both studies. To allow for the comparisons, the categories used are based on the original levels of factors in the first study. The test statistics are shown in Table 3. As expected, the p-values are all less than 0.05, which confirms that the components of respondents in the first study are significantly different from that in the well randomized second study.

Variable	Levels before interacted with Response	G2	df	P-value
Job	White Collar, Blue Collar, Student, House, Unemployed or unknown	861348.2	9	< 0.001
Education	College and more, Lower than College	82340.45	3	< 0.001
Marital	Married, Not married	82723.05	3	< 0.001
Mortgage	Mortgage, No Mortgage	80419.45	3	<0.001
Primary Phone	Cellular, Other	69783.29	3	<0.001

Table 3: Likeliihood ratio test of whether the samples in teh twoo studies are from the same population

Exploratory Data Analysis for Modeling Process

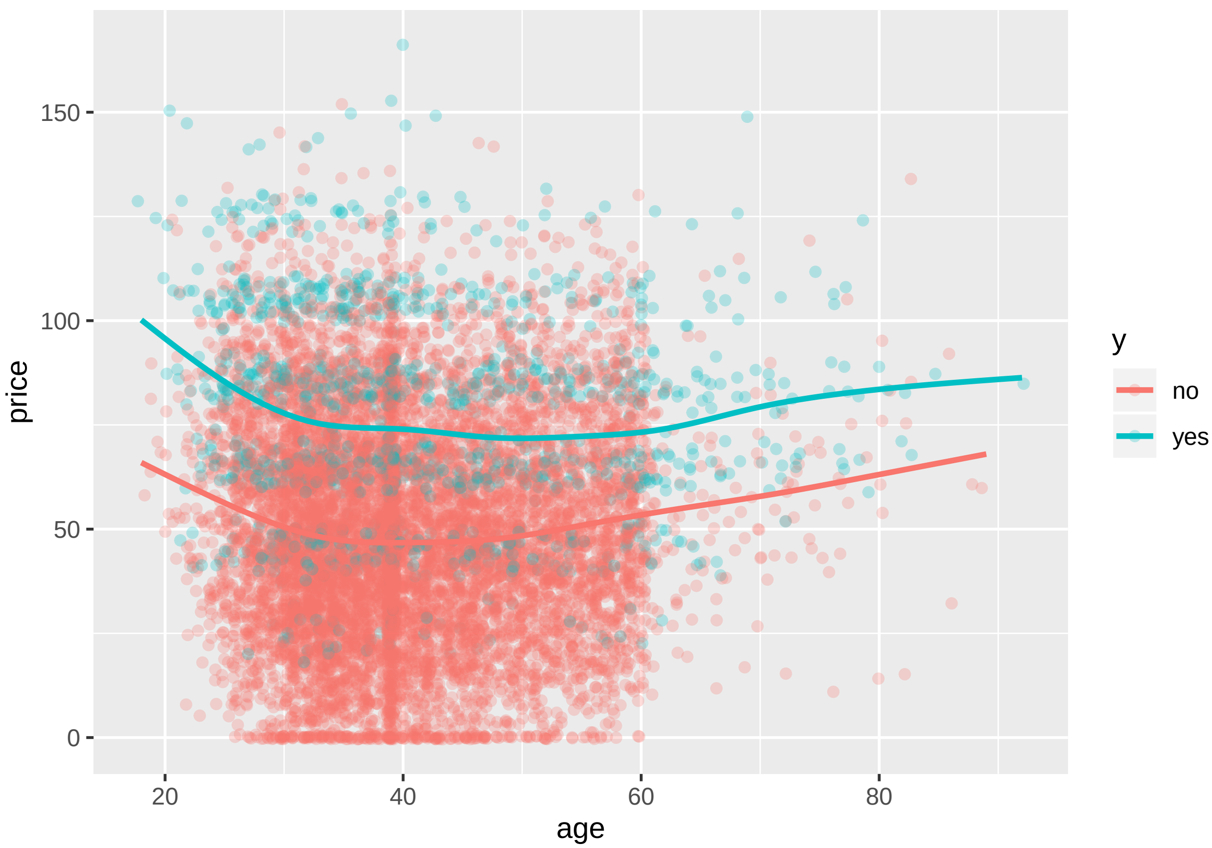
For this study we were interested in creating a logistic model that was able to capture how the likelihood that a person would buy the product based off of their demographic information. This is in effort to create a generalized model that can be used to predict the success of the Toast-USB.

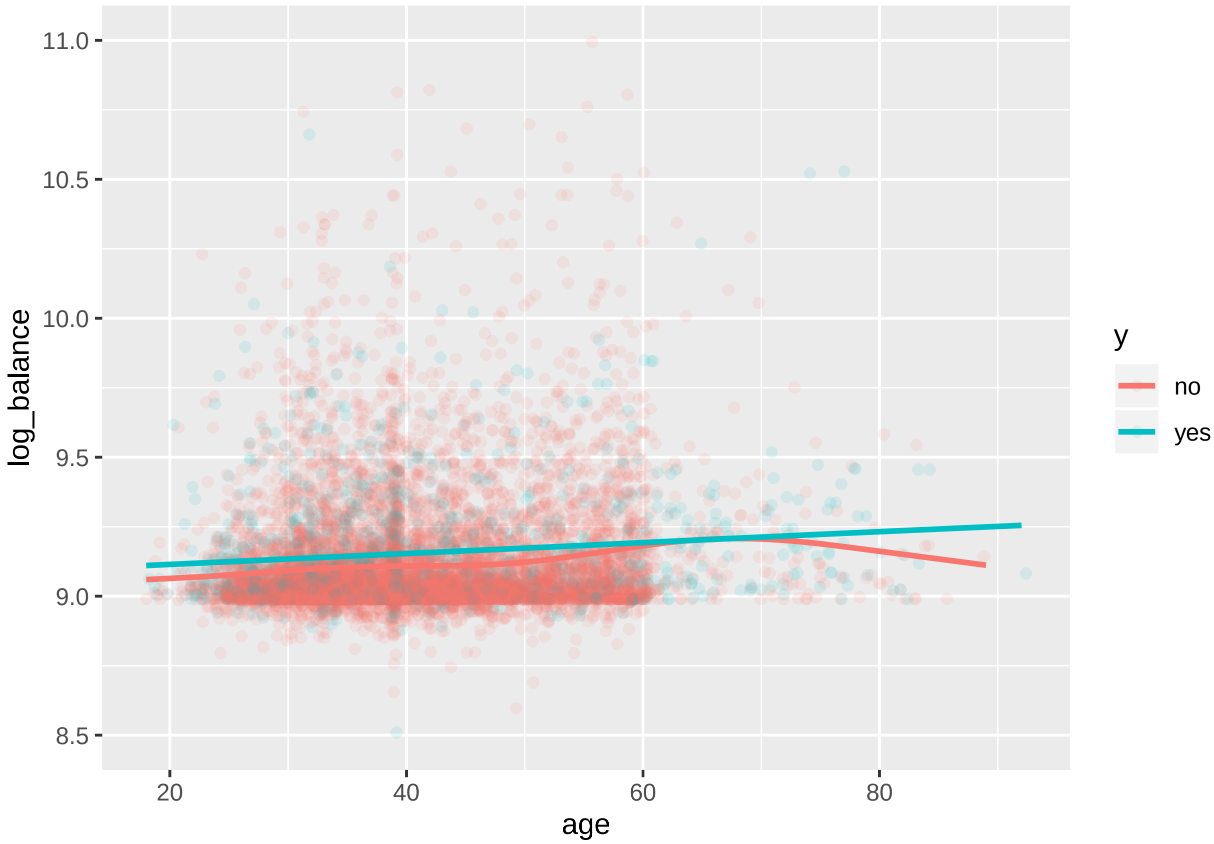
First, we want to explore the relationship between the demographic variables in the sample, and particularly explore how demographic information affects willingness to purchase Toast-USB. In this case, we can define willingness to purchase the Toast-USB as both the binary (Y/N) favorable response and the price a person said they would be willing to pay for the product. Figure X shows the relationship between age and willingness to purchase. There is a moderate relationship between age and price, and the figure suggests that individuals on the older end of the spectrum may actually have more a more favorable response to the product. This is somewhat contridictory to our expectation, given that Millennial and Gen-Z's dual love for technology and gourmet toast served as a compelling reason to enter this market space with the launch of the Toast-USB. This paradoxical relationship could be due to the fact that younger people are more likely to eat-out rather than at home, and therefore are less likely to purchase kitchen appliances. Additionally, young people establishing their first household may have access to less capital to purchase appliances, resulting in a decreased willingness to purchase among this demographic group. The figure also demostrated that people had a favorable response to the product were also, on average, willing to pay more for the product.

Next, in Figure X we explored the relationship between logged-balance and willingness to purchase. Balance representes the amount of non-morgatage credit currently owed by an individual. If a person has a large balance, it could negatively impact their willingness to purchase the Toast-USB simply because they do not have access to capital. The metric representing balance had both negative values and a strong right-skew. We performed a linear shift by the largest negative-value balance and a log-transformation to alleviate the skew of the date. The equation below represents the mathematical formula used to transform the balance variable:

$$TransformedBalance = log(Balance + min(Balance))$$

Figure X represents the association between logged balance and willingness to purchase Toast-USB. The figure does not demonstrate that there is a significant association between balance and willingness to purchase. Similarly to the relationship demonstrated for age, the figure also suggests that people with a favorable respone were, on average, willing to pay more for Toast-USB.


price
150
100
50
0
20
40
60
80
age
y
no
yes



11.0
10.5
10.0
9.5
9.0
8.5
log_balance
20
40
60
80
age
y
no
yes

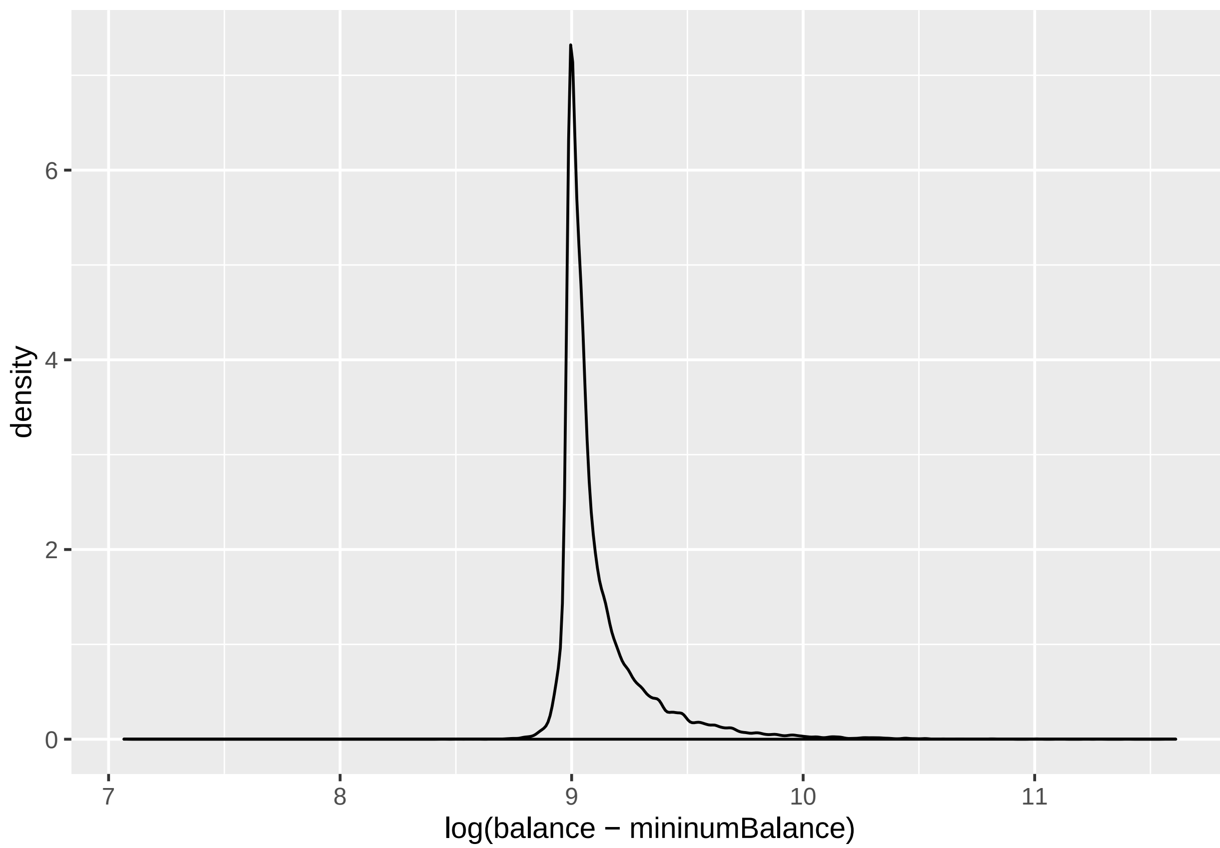


Figure X demostrated the association between continuous demographic predictors and willingness to purchase the product. None of the variables have a particularly strong association with willingness to purchase, and there are no obvious instances of collinearity between the continuous demographic predictors. However, the plots of the continuous predictors do suggest that price is a significant seperator. As demonstrated in previous exploratory analysis, individuals who had a favorable response to the product were also willing to pay more for it than people who did not have an initial favorable response.

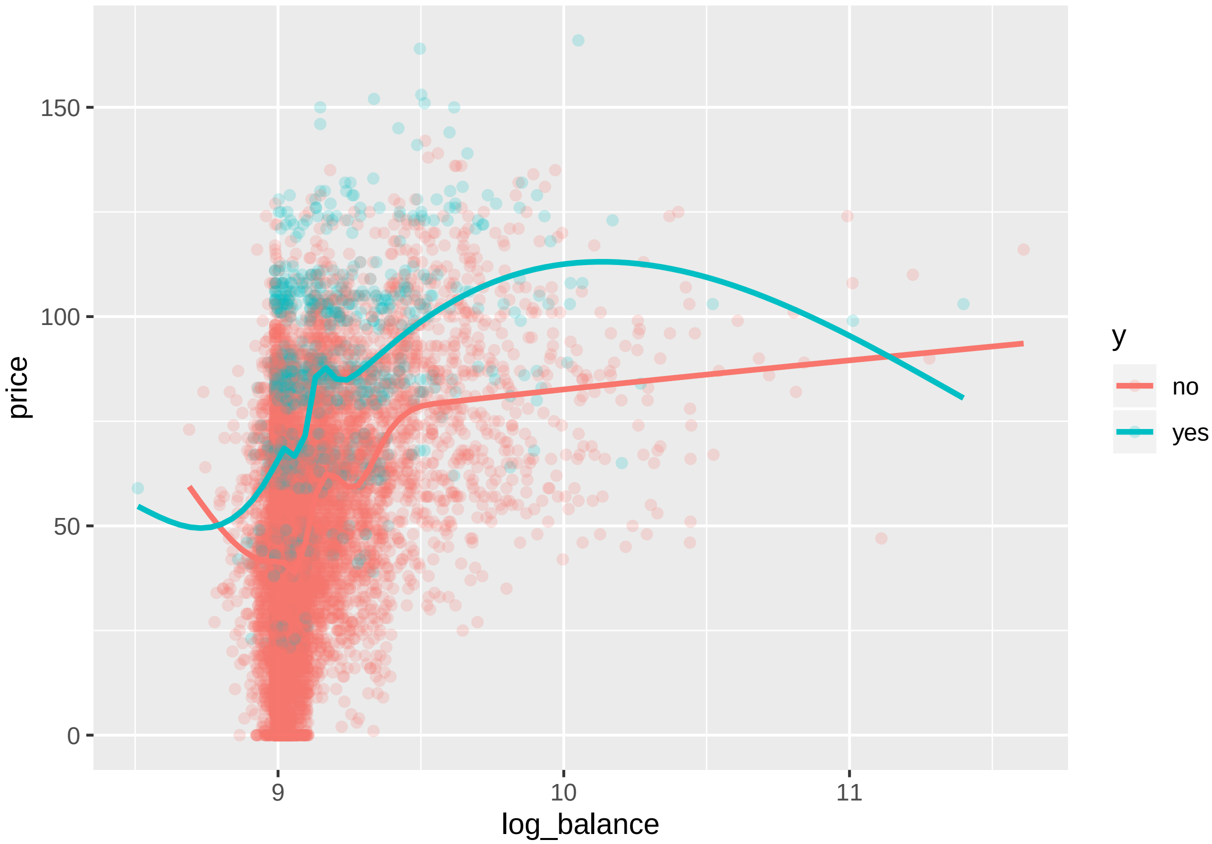
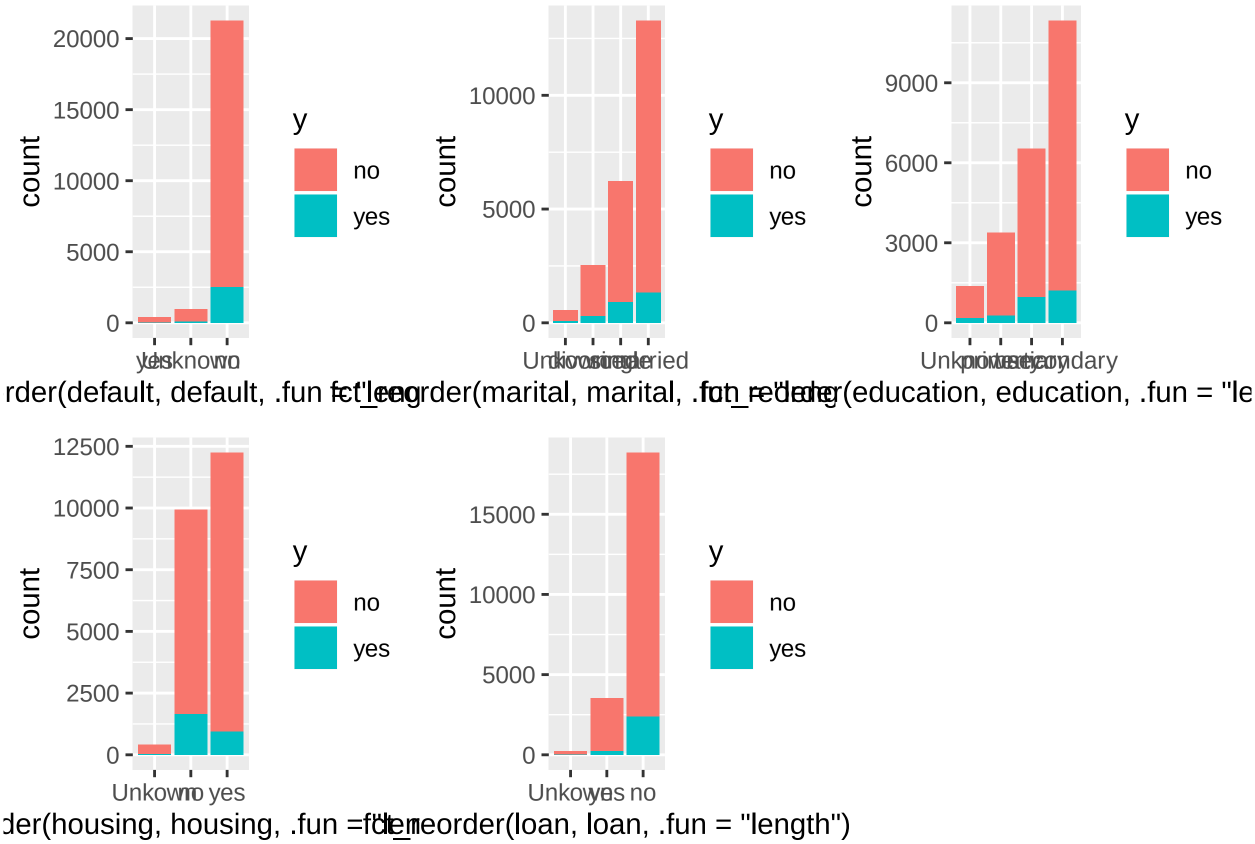
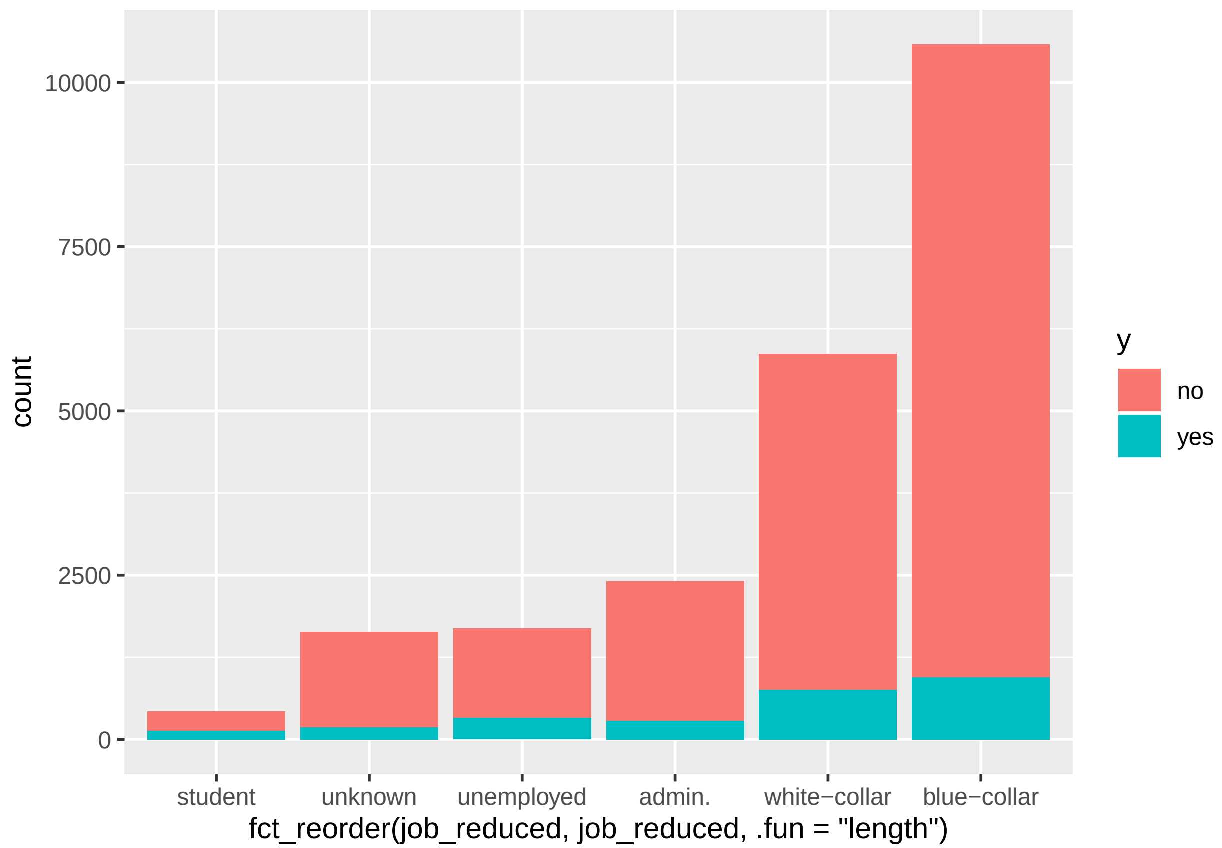


Figure X shows the association between categorical demographic predictors and their willingness to purchase the Toast-USB. Variables representing education, default, and loan have a moderate relationship with willingness to purchase. Individuals with secondary and tertiary education have a higher favorable response rate, which could be dually attributable to access to more capital and cultural trends surrounding gourmet toast that are popular within this group. Additionally, there is a moderate association between willingness to purchase, loan, and default. We believe that these associations could be related, as individuals with secondary and tertiary education (specifically, individuals attended college) are more likely to have a non-morgatage loan due to the exorbanant cost of education in the United States. The association of these three variables should be considered in the structure of the logistic model.



The original dataset obtained by the DOE had 12 factors representing the job classification for individuals in the sample. The job variable was recoded to represent more broad categories more closely related to profession-type. Factor levels in the recoded dataset for profession-type include classifications of student, unknown employment, administration, white-collar, and blue-collar. Figure X represents the distribution of favorable response for each of the profession types. There is no significant association between favorable response and profession type in this sample.



After exploratory analysis, we believe that default, education, loan, and age are demographic variables of interest that could be utilized in the logistic model. For the statistical analysis portion, we aim to build a logistic model that uses relevant demographic variables to predict a favorable response to the Toast-USB and indicate if Toast-Co. should move forward with the launch of the produce.

Model Process

We identified that default, education, loan, and age were potentially significant indicators of willingness to purchase in the exploratory analysis. Our aim for the analysis was to 1) predict the success of the Toast-USB and 2) indicate which demographic groups should be targeted in the marketing campaign. To investigate these endpoints, we generated a function that build a multivariate logistic models representing every combination of the four aforementioned variables. Interaction terms were not included, as none of these variables demonstrated significant collinearity. To do so, we partitioned the data into a test and a train set, both of which represented half of the original dataset (non-overlapping). Using the train-set, we generated 15 potential logistic models representing combinations of these four predictors. Next, we generated a function to cross-validate the models using the test-set to select the model with the maximal likelihood ratio.

```
## y ~age
##      4
```

```
##
## Call:
## glm(formula = bestFormula, family = binomial, data = training)
##
```

```
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.7252  -0.5416  -0.4836  -0.4099   2.5298
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -2.219653   0.119044 -18.646  < 2e-16 ***
## educationprimary   -0.562481   0.100768  -5.582 2.38e-08 ***
## educationsecondary -0.195812   0.084735  -2.311   0.0208 *
## educationtertiary   0.158405   0.086429   1.833   0.0668 .
## loanUnkown         -0.238971   0.217239  -1.100   0.2713
## loanyes            -0.637027   0.070026  -9.097  < 2e-16 ***
## age                 0.009660   0.002016   4.793 1.65e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 16317  on 22604  degrees of freedom
## Residual deviance: 16080  on 22598  degrees of freedom
## AIC: 16094
##
## Number of Fisher Scoring iterations: 5
```

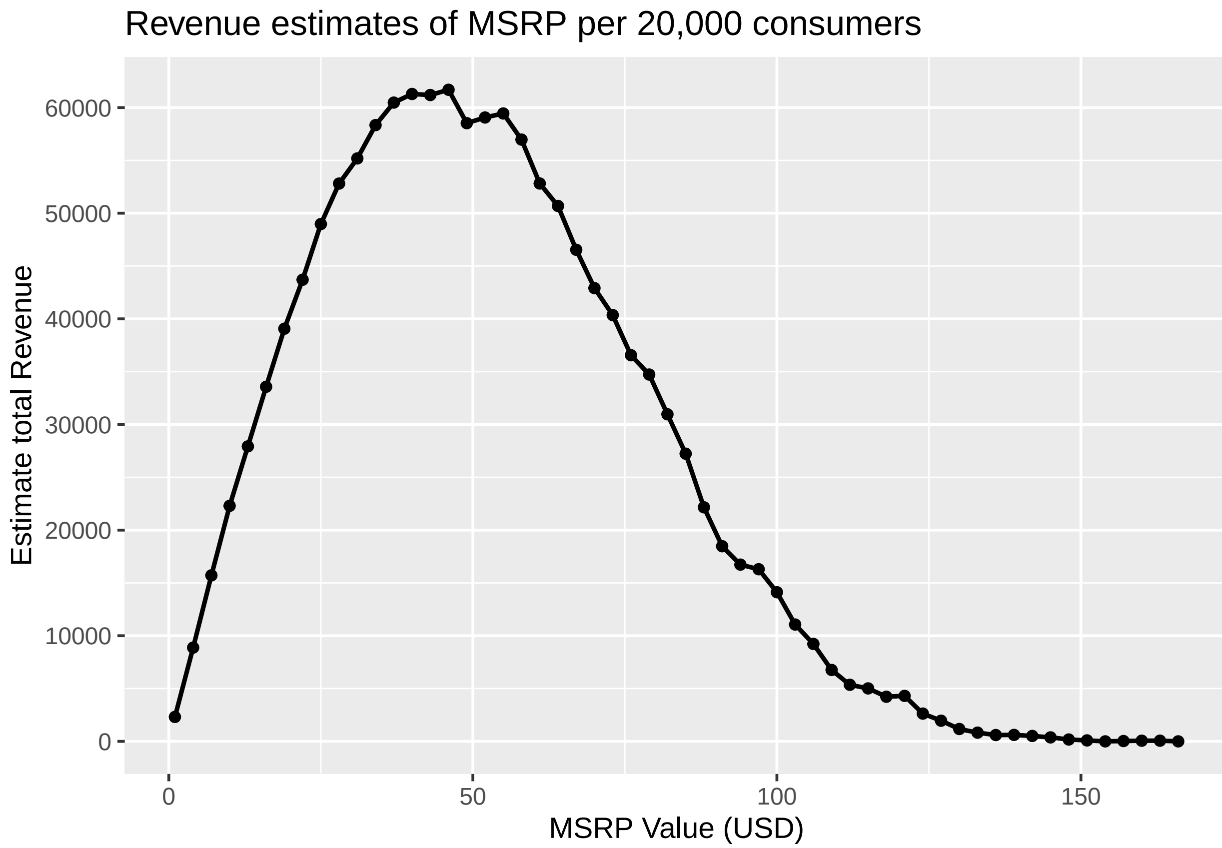
Of the 15 logistic models that were generated using loan, age, default, and education, we found that the multivariate logistic model regressing age, loan, and education on response to Toast-USB had the maximum likelihood ratio. The model summary also indicated that secondary, tertiary and unknown education, age, a having a loan were significant predictors in the model. Thus, we believe that education, loan status, and age will be demographic variables of interest to Toast-Co for strategizing their marketing campaign. Next,we used our selected logistic model to simulate a response rate using the testing set.

```
## [1] 0.1186463
```

The favorable response rate for for the product was 12.14%, which is approximately half of the necessary response rate that Toast-Co. indicated would be necessary for the launch of the product. Based on this analysis, we do not recommend that Toast Co. move forward with this version to Toast-USB.

SA3 Application of Model to Determine MSRP

From our previous section we discovered that the logistic model containing loan,education,age as our predictor variables performed the best predictions. Although the favorable response is not near the break even rate we still continued in determining which MSRP value would be able to maximize revenue. To generate a range of reasonable prices we selected the minimum and maximum value of price answered in the survey. The lowest value responded value was 0 but we will start our search at 1 and the maximum responded price was 168 so we will search for the optimal value in that range. To find the maximum price we performed the following simulation: For each potential MSRP Value: Repeat the below following process 5 times and take the average: For each observation in our training set: 1. Generate a probability they would purchase the product using the logistic model 2. Compare that generated probability with a randomly generated number, if the random number is lower than the probability then the customer will consider purchasing the item. If not then we skip to next observation. 3. We compare the MSRP to observed price the customer said they were willing to pay. If the MSRP is less than than the price then in our simulation the customer "purchases" the product and that sale is added to the total revenue and we continue to the next observation. We key the total revenue to be associated with the MSRP value and selected the MSRP value with the highest revenue.



From the results of our simulation we can see that the estimated maximum MSRP Value would $46. The simulation was ran on a test set containing 20,000 observations. From this we could estimate that for every 20,000 people that interact with our product we could estimate a revenue of approximately $60,000.

Conclusion: