DATA 621 - HW4

Andrew Bowen, Glen Davis, Shoshana Farber, Joshua Forster, Charles Ugiagbe

2023-10-30

Homework 4 - Binary Logistic Regression & Multiple Linear Regression

Data Exploration:

We load an auto insurance company dataset containing 8,161 records. Each record represents a customer, and each record has two response variables: `TARGET_FLAG` and `TARGET_AMT`. Below is a short description of all the variables of interest in the data set, including these response variables:

VARIABLE NAME	DEFINITION
`INDEX`	Identification Variable
`TARGET_FLAG`	Was Car in a crash? 1=YES 0=NO
`TARGET_AMT`	If car was in a crash, what was the cost
`AGE`	Age of Driver
`BLUEBOOK`	Value of Vehicle
`CAR_AGE`	Vehicle Age
`CAR_TYPE`	Type of Car
`CAR_USE`	Vehicle Use
`CLM_FREQ`	# Claims (Past 5 Years)
`EDUCATION`	Max Education Level
`HOMEKIDS`	# Children at Home
`HOME_VAL`	Home Value
`INCOME`	Income
`JOB`	Job Category
`KIDSDRIV`	# Driving Children
`MSTATUS`	Marital Status
`MVR_PTS`	Motor Vehicle Record Points
`OLDCLAIM`	Total Claims (Past 5 Years)
`PARENT1`	Single Parent
`RED_CAR`	A Red Car
`REVOKED`	License Revoked (Past 7 Years)
`SEX`	Gender
`TIF`	Time in Force
`TRAVTIME`	Distance to Work
`URBANICITY`	Home/Work Area
`YOJ`	Years on Job

We take a look at the classes of our variables.

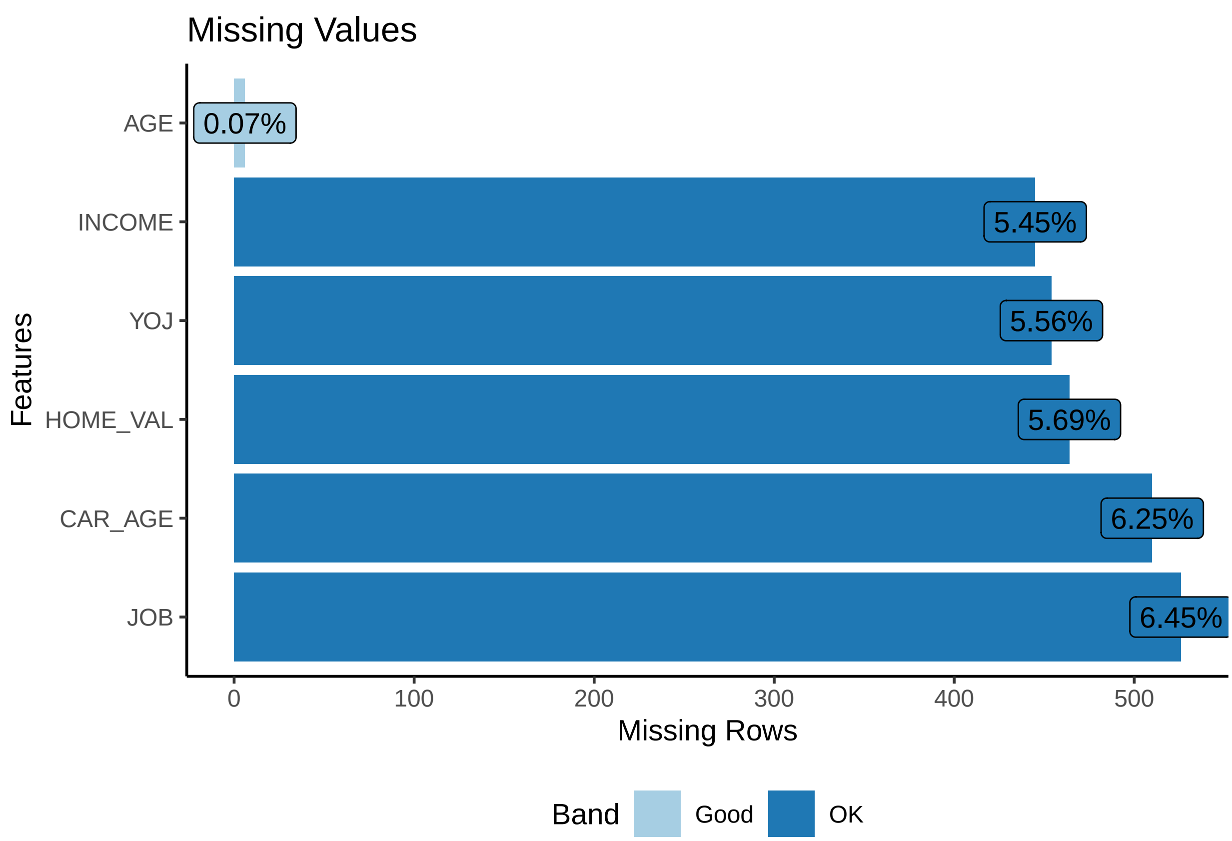
Class	Count	Variables
character	14	BLUEBOOK, CAR_TYPE, CAR_USE, EDUCATION, HOME_VAL, INCOME, JOB, MSTATUS, C
integer	11	AGE, CAR_AGE, CLM_FREQ, HOMEKIDS, INDEX, KIDSDRIV, MVR_PTS, TARGET_FLAG,
numeric	1	TARGET_AMT

`INCOME`, `HOME_VAL`, `BLUEBOOK`, and `OLDCLAIM` are all character columns that need to be recoded as integers. `TARGET_FLAG` and the remaining character columns will all need to be recoded as factors.

We remove the identification variable `INDEX` and take a look at a summary of the dataset's completeness.

rows	8161
columns	25
all_missing_columns	0
total_missing_values	2405
complete_rows	6045

None of our columns are completely devoid of data. There are 6,045 complete rows in the dataset, which is about 74% of our observations. There are 2,405 total missing values. We take a look at which variables contain these missing values and what the spread is.



A very small percentage of observations contain missing `AGE` values. The `INCOME`, `YOJ`, `HOME_VAL`, `CAR_AGE`, and `JOB` variables are each missing around 5.5 to 6.5 percent of values. There are no variables containing such extreme proportions of missing values that removal would be warranted on that basis alone.

We have 14 numerical variables and 11 categorical variables (including the dummy variable `TARGET_FLAG`). We recode the categorical variables as factors and list the possible ranges or values for each variable in the breakdown below:

Variable	Type	Values
AGE	Numeric	16 - 81
BLUEBOOK	Numeric	1500 - 69740
CAR_AGE	Numeric	-3 - 28
CLM_FREQ	Numeric	0 - 5
HOME_VAL	Numeric	0 - 885282
HOMEKIDS	Numeric	0 - 5
INCOME	Numeric	0 - 367030
KIDSDRIV	Numeric	0 - 4
MVR_PTS	Numeric	0 - 13
OLDCLAIM	Numeric	0 - 57037
TARGET_AMT	Numeric	0 - 107586.1
TIF	Numeric	1 - 25
TRAVTIME	Numeric	5 - 142
YOJ	Numeric	0 - 23
CAR_TYPE	Categorical	Minivan, Panel Truck, Pickup, Sports Car, Van, z_SUV
CAR_USE	Categorical	Commercial, Private
EDUCATION	Categorical	<High School, Bachelors, Masters, PhD, z_High School
JOB	Categorical	Clerical, Doctor, Home Maker, Lawyer, Manager, Professional, Student, z_Blue Collar
MSTATUS	Categorical	Yes, z_No
PARENT1	Categorical	No, Yes
RED_CAR	Categorical	no, yes
REVOKED	Categorical	No, Yes
SEX	Categorical	M, z_F
TARGET_FLAG	Categorical	0, 1
URBANICITY	Categorical	Highly Urban/ Urban, z_Highly Rural/ Rural

TK: Some of the factor levels are named inconsistently, so we rename those.

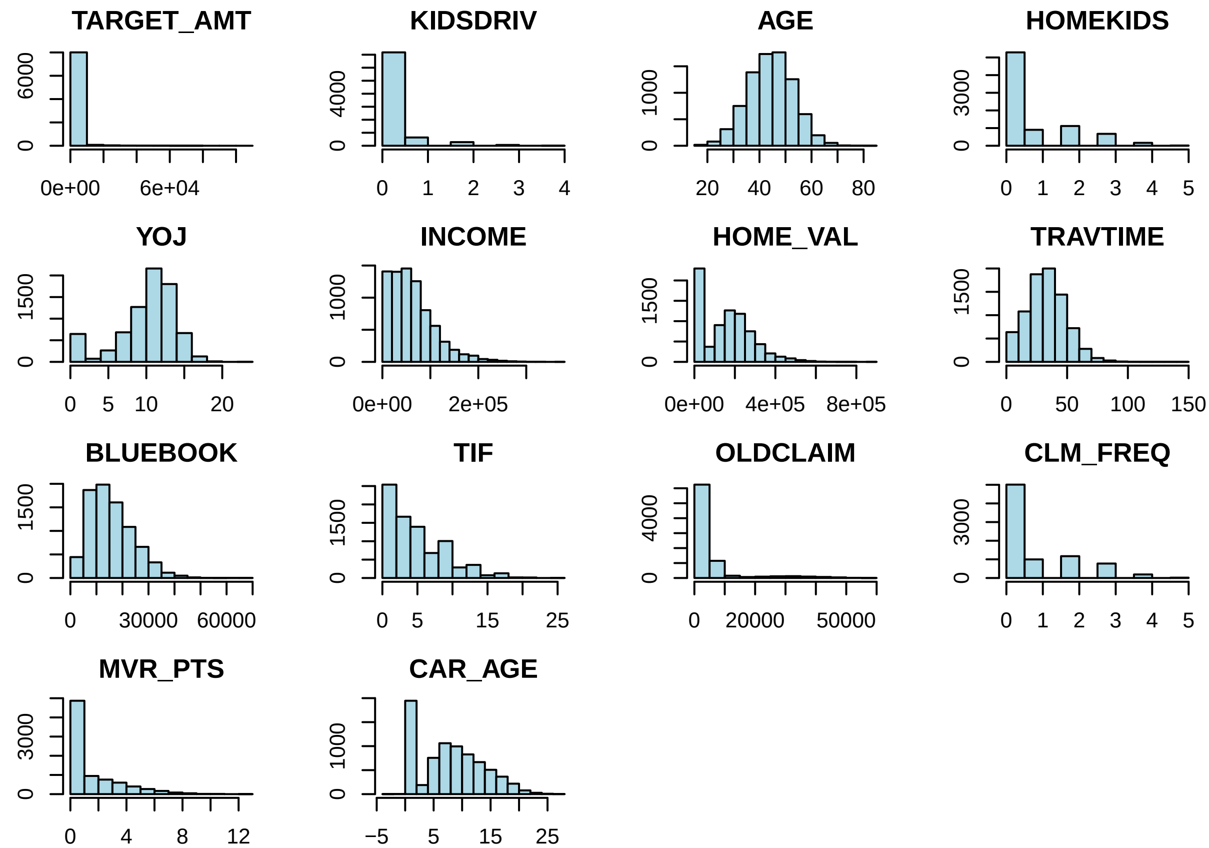
Let's take a look at the summary statistics for each variable.

```
##  TARGET_FLAG   TARGET_AMT        KIDSDRIV           AGE           HOMEKIDS
##  0:6008      Min.   :     0   Min.   :0.0000   Min.   :16.00   Min.   :0.0000
##  1:2153      1st Qu.:     0   1st Qu.:0.0000   1st Qu.:39.00   1st Qu.:0.0000
##              Median :     0   Median :0.0000   Median :45.00   Median :0.0000
##              Mean   :  1504   Mean   :0.1711   Mean   :44.79   Mean   :0.7212
##              3rd Qu.:  1036   3rd Qu.:0.0000   3rd Qu.:51.00   3rd Qu.:1.0000
##              Max.   :107586   Max.   :4.0000   Max.   :81.00   Max.   :5.0000
##                                                NA's   :6
##       YOJ           INCOME       PARENT1       HOME_VAL      MSTATUS
##  Min.   : 0.0   Min.   :     0   No :7084   Min.   :     0   Yes :4894
##  1st Qu.: 9.0   1st Qu.: 28097   Yes:1077   1st Qu.:     0   z_No:3267
##  Median :11.0   Median : 54028              Median :161160
##  Mean   :10.5   Mean   : 61898              Mean   :154867
##  3rd Qu.:13.0   3rd Qu.: 85986              3rd Qu.:238724
##  Max.   :23.0   Max.   :367030              Max.   :885282
##  NA's   :454    NA's   :445                 NA's   :464
##   SEX                EDUCATION                JOB          TRAVTIME
##  M  :3786   <High School :1203   z_Blue Collar:1825   Min.   :  5.00
```

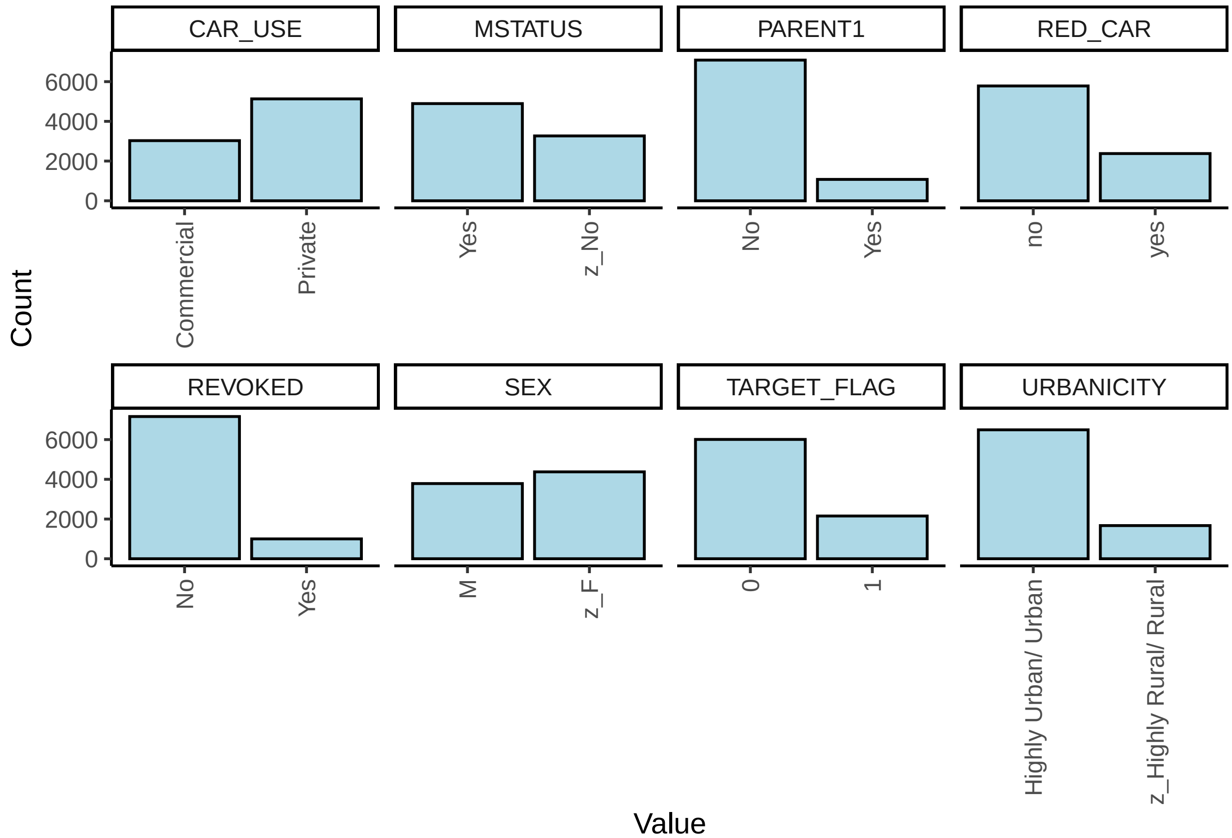
```
##  z_F:4375   Bachelors    :2242   Clerical     :1271   1st Qu.: 22.00
##             Masters      :1658   Professional :1117   Median : 33.00
##             PhD          : 728   Manager      : 988   Mean   : 33.49
##             z_High School:2330   Lawyer       : 835   3rd Qu.: 44.00
##                                  (Other)      :1599   Max.   :142.00
##                                  NA's         : 526
##       CAR_USE        BLUEBOOK          TIF              CAR_TYPE
##  Commercial:3029   Min.   : 1500   Min.   : 1.000   Minivan    :2145
##  Private   :5132   1st Qu.: 9280   1st Qu.: 1.000   Panel Truck: 676
##                    Median :14440   Median : 4.000   Pickup     :1389
##                    Mean   :15710   Mean   : 5.351   Sports Car : 907
##                    3rd Qu.:20850   3rd Qu.: 7.000   Van        : 750
##                    Max.   :69740   Max.   :25.000   z_SUV      :2294
##
##  RED_CAR       OLDCLAIM        CLM_FREQ      REVOKED       MVR_PTS
##  no :5783   Min.   :    0   Min.   :0.0000   No :7161   Min.   : 0.000
##  yes:2378   1st Qu.:    0   1st Qu.:0.0000   Yes:1000   1st Qu.: 0.000
##             Median :    0   Median :0.0000              Median : 1.000
##             Mean   : 4037   Mean   :0.7986              Mean   : 1.696
##             3rd Qu.: 4636   3rd Qu.:2.0000              3rd Qu.: 3.000
##             Max.   :57037   Max.   :5.0000              Max.   :13.000
##
##     CAR_AGE                       URBANICITY
##  Min.   :-3.000   Highly Urban/ Urban  :6492
##  1st Qu.: 1.000   z_Highly Rural/ Rural:1669
##  Median : 8.000
##  Mean   : 8.328
##  3rd Qu.:12.000
##  Max.   :28.000
##  NA's   :510
```

There are 6 NAs in `AGE`, 454 in `YOJ`, and 510 in `CAR_AGE`.

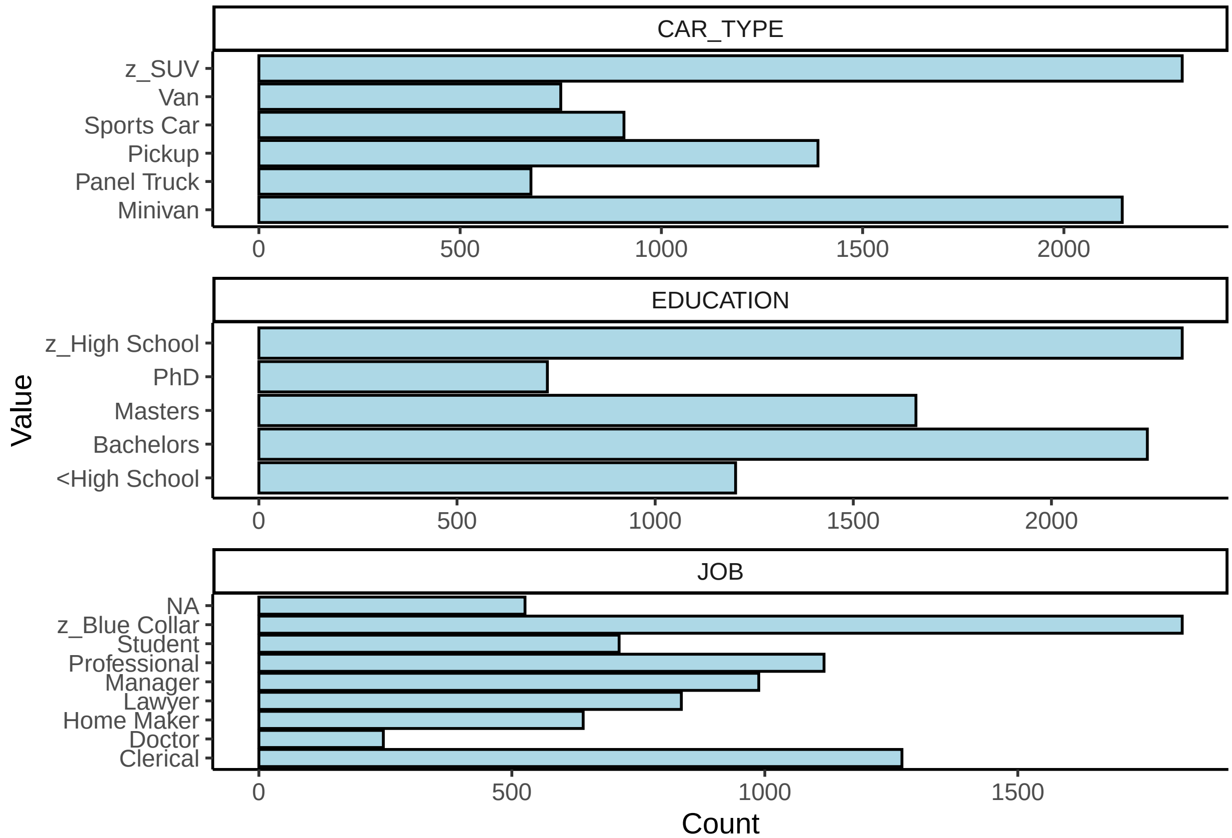
Let's take a look at the distributions of the numeric variables.



Let's also take a look at the distributions of the categorical variables. First, we look at the distributions for categorical variables with only two levels.



Next we look at the distributions for the categorical variables with more than two levels.



Data Preparation

We split the data into a train and test set.

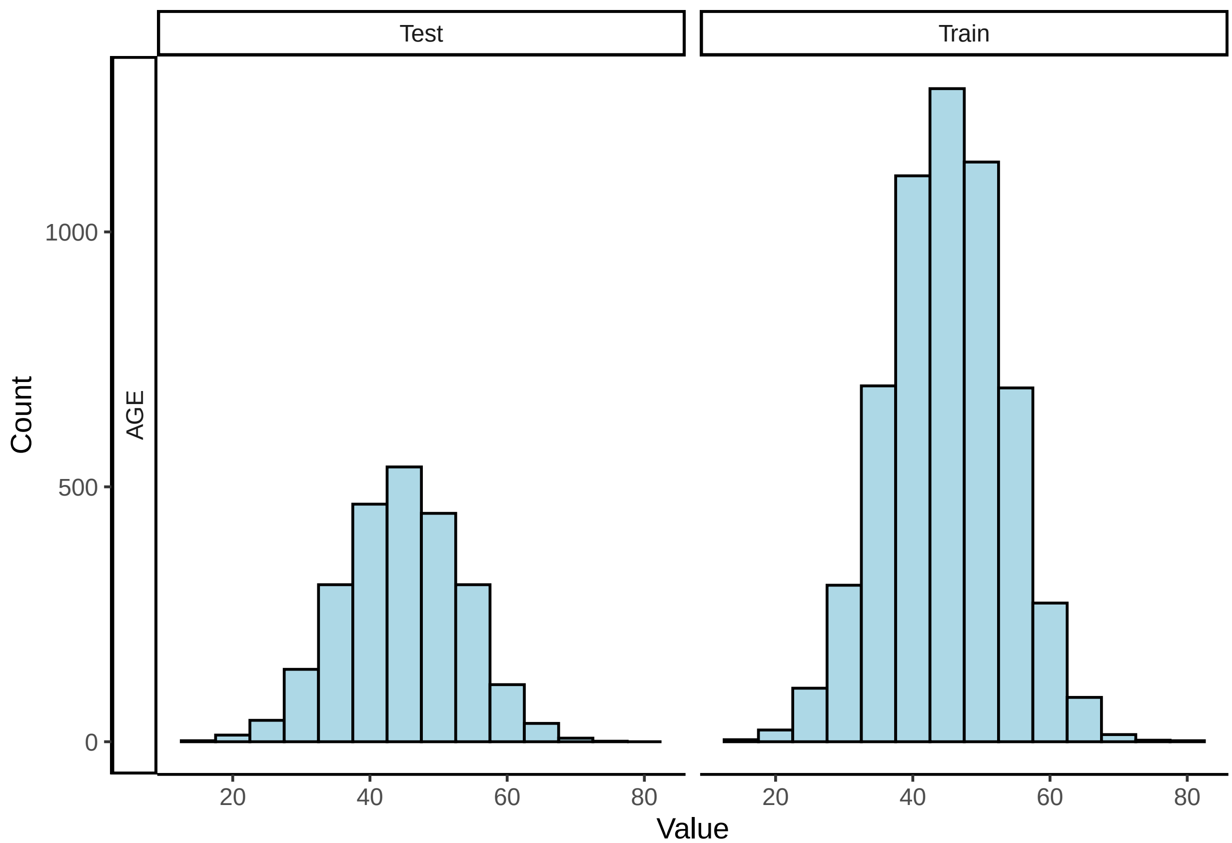
We impute missing data in the train and test sets using the `mice` package for five numeric variables (`AGE`, `INCOME`, `YOJ`, `HOME_VAL`, and `CAR_AGE`) and one categorical variable (`JOB`). For the numeric variables, we use the package's `pmm` (predictive mean matching) method, and for the categorical variable, we use the package's `polyreg` (polytomous, i.e. multinomial, logistic regression) method.

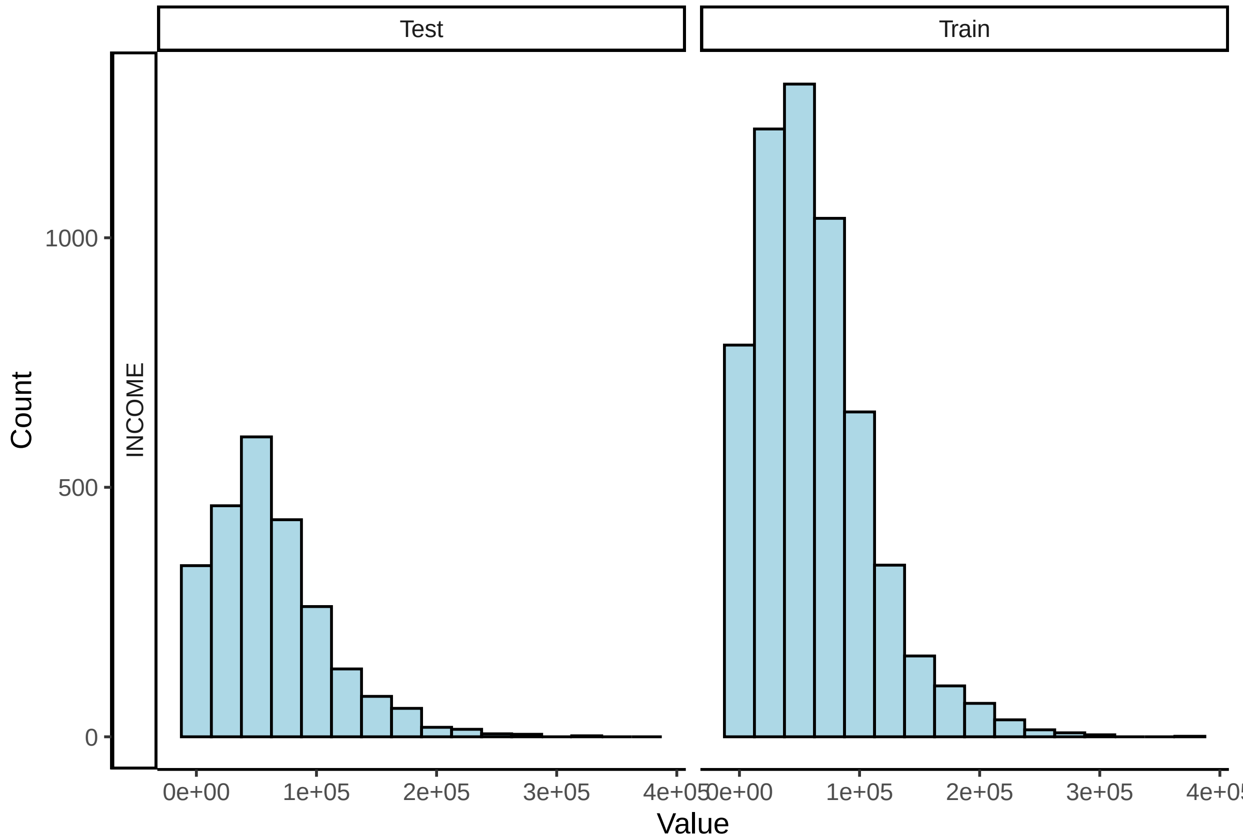
We confirm there are no longer any missing values in the train or test datasets.

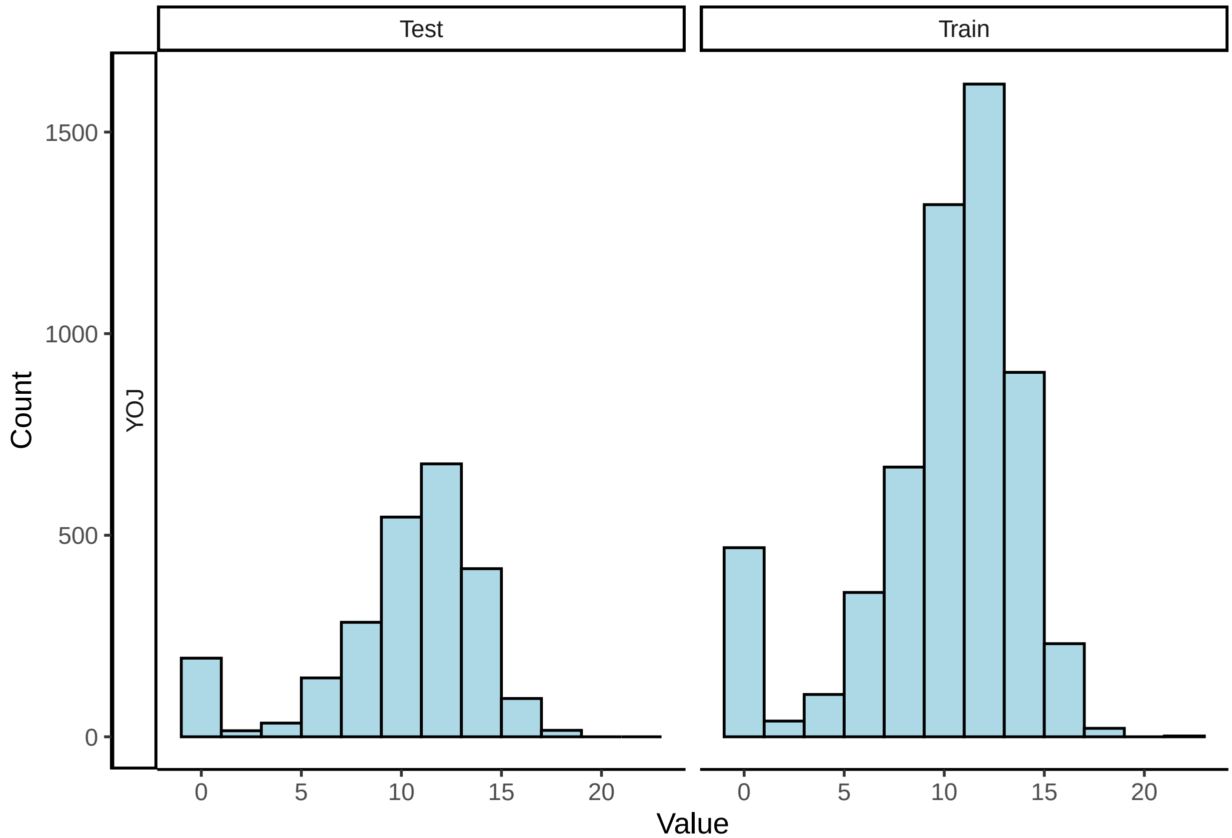
```
## [1] TRUE
```

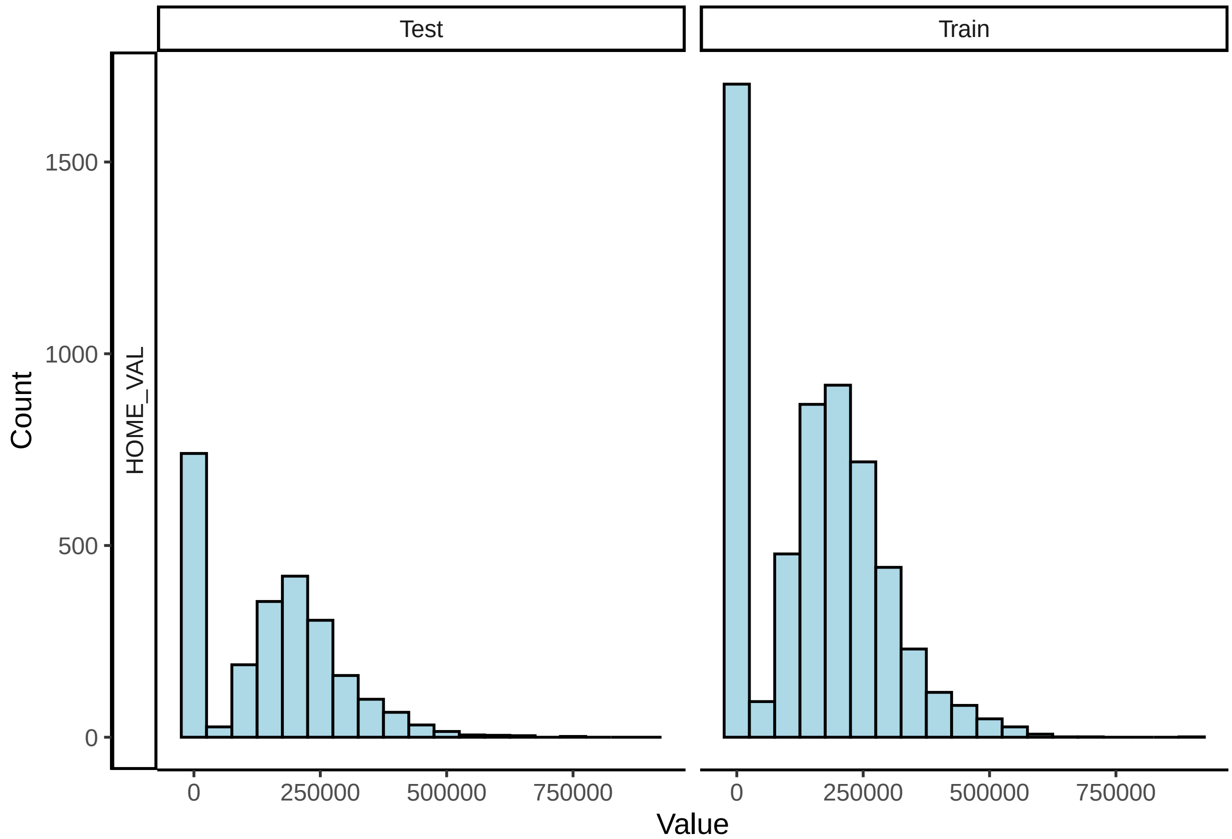
We take a look at the distributions for our imputed variables to see if the distributions of these variables in the train and test sets differ from what we originally observed or between sets.

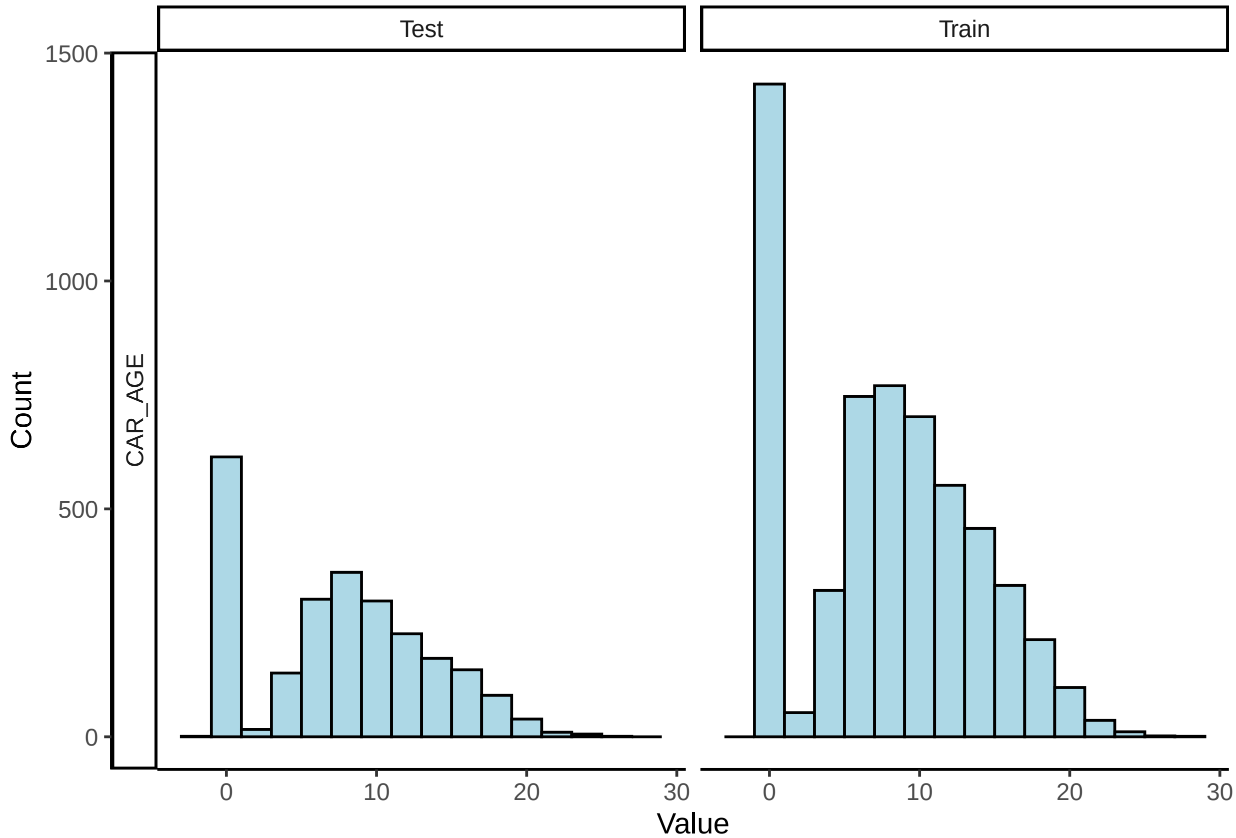
First, we examine the five numerical variables we imputed.


Test
Train
Count
AGE
1000
500
0
20
40
60
80
20
40
60
80
Value

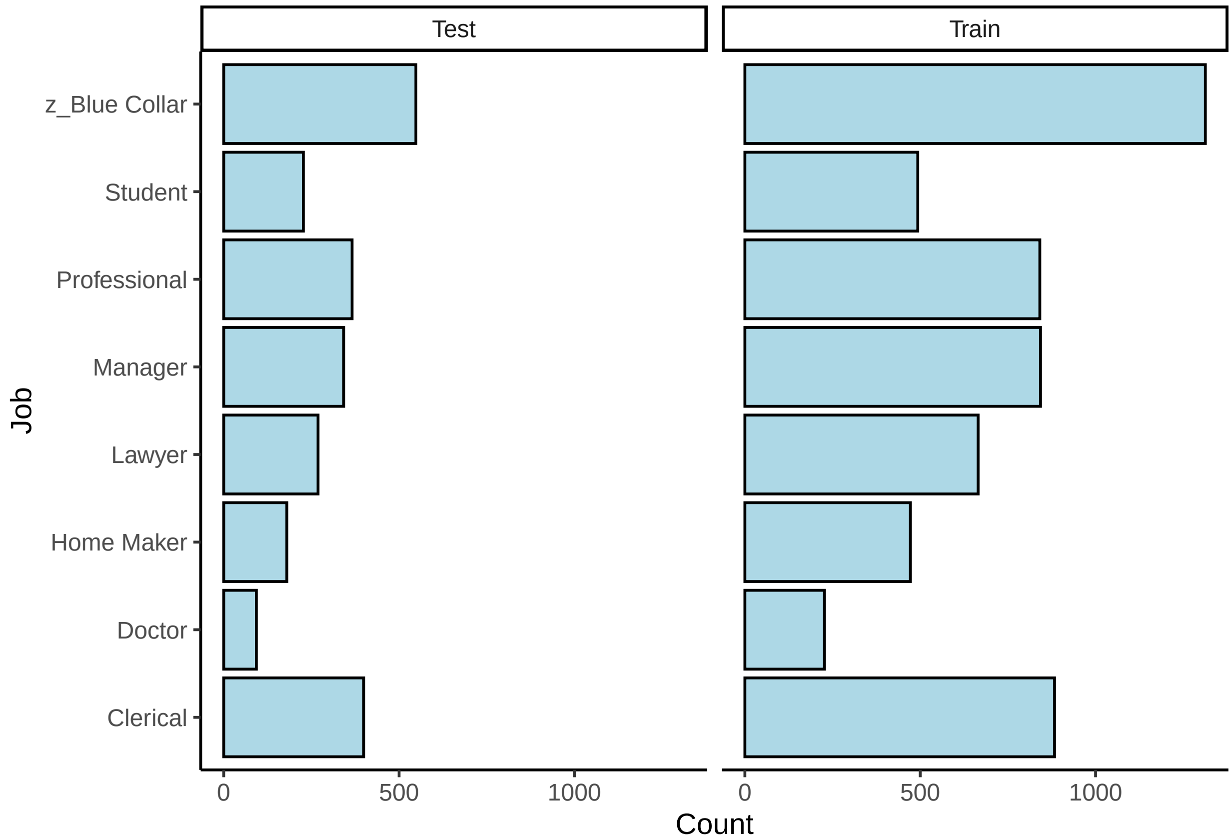

Test
Train
INCOME
Count
1000
500
0
0e+00
1e+05
2e+05
3e+05
4e+05
Value


Test
Train
YOJ
Count
1500
1000
500
0
0
5
10
15
20
Value


Test
Train
Count
HOME_VAL
1500
1000
500
0
0
250000
500000
750000
0
250000
500000
750000
Value



Next we look at the single categorical variable we imputed.



Build Models

Select Models

Appendix: Report Code

Below is the code for this report to generate the models and charts above.

```
knitr::opts_chunk$set(echo = FALSE)
library(tidyverse)
library(DataExplorer)
library(knitr)
library(mice)
library(cowplot)

cur_theme <- theme_set(theme_classic())

my_url <- "https://raw.githubusercontent.com/andrewbowen19/businessAnalyticsDataMiningDATA621/main/data/
main_df <- read.csv(my_url, na.strings = "")

classes <- as.data.frame(unlist(lapply(main_df, class))) |>
    rownames_to_column()
cols <- c("Variable", "Class")
colnames(classes) <- cols
classes_summary <- classes |>
```

```
    group_by(Class) |>
    summarize(Count = n(),
              Variables = paste(sort(unique(Variable)),collapse=", "))
knitr::kable(classes_summary, format = "simple")

vars <- c("INCOME", "HOME_VAL", "BLUEBOOK", "OLDCLAIM")
main_df <- main_df |>
    mutate(across(all_of(vars), ~gsub("\\$|,", "", .) |> as.integer()))

main_df <- main_df |>
    select(-INDEX)
remove <- c("discrete_columns", "continuous_columns",
            "total_observations", "memory_usage")
completeness <- introduce(main_df) |>
    select(-all_of(remove))
knitr::kable(t(completeness), format = "simple")

p1 <- plot_missing(main_df, missing_only = TRUE,
                   ggtheme = theme_classic(), title = "Missing Values")

p1 <- p1 +
    scale_fill_brewer(palette = "Paired")
p1

output <- split_columns(main_df, binary_as_factor = TRUE)
num <- data.frame(Variable = names(output$continuous),
                   Type = rep("Numeric", ncol(output$continuous)))
cat <- data.frame(Variable = names(output$discrete),
                   Type = rep("Categorical", ncol(output$discrete)))
ranges <- as.data.frame(t(sapply(main_df |> select(-names(output$discrete)),
                                 range, na.rm = TRUE)))
factors <- names(output$discrete)
main_df <- main_df |>
    mutate(across(all_of(factors), ~as.factor(.)))
values <- as.data.frame(t(sapply(main_df |> select(all_of(factors)),
                                 levels)))
values <- values |>
    mutate(across(all_of(factors), ~toString(unlist(.))))
values <- as.data.frame(t(values)) |>
    rownames_to_column()
cols <- c("Variable", "Values")
colnames(values) <- cols
remove <- c("V1", "V2")
ranges <- ranges |>
    rownames_to_column() |>
    group_by(rowname) |>
    mutate(Values = toString(c(V1, " - ", round(V2, 1))),
           Values = str_replace_all(Values, ",", "")) |>
    select(-all_of(remove))
colnames(ranges) <- cols
num <- num |>
    merge(ranges)
cat <- cat |>
```

```r
    merge(values)
num_vs_cat <- num |>
    bind_rows(cat)
knitr::kable(num_vs_cat, format = "simple")

summary(main_df)

# just numeric variables
numeric_train <- main_df[,sapply(main_df, is.numeric)]
par(mfrow=c(4,4))
par(mai=c(.3,.3,.3,.3))
variables <- names(numeric_train)
for (i in 1:(length(variables))) {
  hist(numeric_train[[variables[i]]], main = variables[i], col = "lightblue")
}

cat_pivot <- main_df |>
    select(all_of(factors)) |>
    pivot_longer(cols = all_of(factors),
                 names_to = "Variable",
                 values_to = "Value") |>
    group_by(Variable, Value) |>
    summarize(Count = n()) |>
    group_by(Variable) |>
    mutate(Levels = n()) |>
    ungroup()
p2 <- cat_pivot |>
    filter(Levels == 2) |>
    ggplot(aes(x = Value, y = Count)) +
    geom_col(fill = "lightblue", color = "black") +
    facet_wrap(vars(Variable), ncol = 4, scales = "free_x") +
    theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
p2

p3 <- cat_pivot |>
    filter(Levels > 2) |>
    ggplot(aes(x = Value, y = Count)) +
    geom_col(fill = "lightblue", color = "black") +
    coord_flip() +
    facet_wrap(vars(Variable), ncol = 1, scales = "free")
p3

set.seed(202)
rows <- sample(nrow(main_df))
main_df <- main_df[rows, ]
sample <- sample(c(TRUE, FALSE), nrow(main_df), replace=TRUE,
                 prob=c(0.7,0.3))
train_df <- main_df[sample, ]
test_df <- main_df[!sample, ]

#Start with train_df
init = mice(train_df, maxit=0)
meth = init$method
```

```
predM = init$predictorMatrix

#Skip variables without missing data
missing <- c("AGE", "INCOME", "YOJ", "HOME_VAL", "CAR_AGE", "JOB")
x <- names(main_df)
not_missing <- x[!x %in% missing]
meth[not_missing] = ""

#Set different imputation methods for each of the variables with missing data
meth[c("AGE")] = "pmm" #Predictive mean matching
meth[c("INCOME")] = "pmm"
meth[c("YOJ")] = "pmm"
meth[c("HOME_VAL")] = "pmm"
meth[c("CAR_AGE")] = "pmm"
meth[c("JOB")] = "polyreg" #Polytomous (multinomial) logistic regression

#Impute
imputed = mice(train_df, method=meth, predictorMatrix=predM, m=5,
               printFlag = FALSE)
train_df_imputed <- complete(imputed)

#Repeat for test_df
init = mice(test_df, maxit=0)
meth = init$method
predM = init$predictorMatrix
meth[not_missing] = ""
meth[c("AGE")] = "pmm"
meth[c("INCOME")] = "pmm"
meth[c("YOJ")] = "pmm"
meth[c("HOME_VAL")] = "pmm"
meth[c("CAR_AGE")] = "pmm"
meth[c("JOB")] = "polyreg"
imputed = mice(test_df, method=meth, predictorMatrix=predM, m=5,
               printFlag = FALSE)
test_df_imputed <- complete(imputed)

x <- sapply(train_df_imputed, function(x) sum(is.na(x)))
y <- sapply(test_df_imputed, function(x) sum(is.na(x)))
sum(x, y) == 0

job <- c("JOB")
imp_train_num <- train_df_imputed |>
    select(all_of(missing[!missing %in% job])) |>
    mutate(Set = "Train")
imp_test_num <- test_df_imputed |>
    select(all_of(missing[!missing %in% job])) |>
    mutate(Set = "Test")
imp_num <- imp_train_num |>
    bind_rows(imp_test_num)
imp_num_pivot <- imp_num |>
    pivot_longer(!Set, names_to = "Variable", values_to = "Value")
p4a <- imp_num_pivot |>
    filter(Variable == "AGE") |>
```

```
    ggplot(aes(x = Value)) +
    geom_histogram(fill = "lightblue", color = "black", binwidth = 5) +
    labs(y = "Count") +
    facet_grid(rows = vars(Variable), cols = vars(Set),
               switch = "y")
p4b <- imp_num_pivot |>
    filter(Variable == "INCOME") |>
    ggplot(aes(x = Value)) +
    geom_histogram(fill = "lightblue", color = "black", binwidth = 25000) +
    labs(y = "Count") +
    facet_grid(rows = vars(Variable), cols = vars(Set),
               switch = "y")
p4c <- imp_num_pivot |>
    filter(Variable == "YOJ") |>
    ggplot(aes(x = Value)) +
    geom_histogram(fill = "lightblue", color = "black", binwidth = 2) +
    labs(y = "Count") +
    facet_grid(rows = vars(Variable), cols = vars(Set),
               switch = "y")
p4d <- imp_num_pivot |>
    filter(Variable == "HOME_VAL") |>
    ggplot(aes(x = Value)) +
    geom_histogram(fill = "lightblue", color = "black", binwidth = 50000) +
    labs(y = "Count") +
    facet_grid(rows = vars(Variable), cols = vars(Set),
               switch = "y")
p4e <- imp_num_pivot |>
    filter(Variable == "CAR_AGE") |>
    ggplot(aes(x = Value)) +
    geom_histogram(fill = "lightblue", color = "black", binwidth = 2) +
    labs(y = "Count") +
    facet_grid(rows = vars(Variable), cols = vars(Set),
               switch = "y")
p4a
p4b
p4c
p4d
p4e

imp_train_pivot_cat <- train_df_imputed |>
    select(all_of(missing)) |>
    pivot_longer(cols = all_of(job),
                 names_to = "Variable",
                 values_to = "Value") |>
    group_by(Variable, Value) |>
    summarize(Count = n()) |>
    mutate(Set = "Train")
imp_test_pivot_cat <- test_df_imputed |>
    select(all_of(missing)) |>
    pivot_longer(cols = all_of(job),
                 names_to = "Variable",
                 values_to = "Value") |>
    group_by(Variable, Value) |>
```

```
    summarize(Count = n()) |>
    mutate(Set = "Test")
imp_pivot_cat <- imp_train_pivot_cat |>
    bind_rows(imp_test_pivot_cat)
p4f <- imp_pivot_cat |>
    ggplot(aes(x = Value, y = Count)) +
    geom_col(fill = "lightblue", color = "black") +
    labs(x = "Job") +
    coord_flip() +
    facet_wrap(vars(Set), ncol = 2)
p4f
```