

Balance Prediction Linear Regression

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21 December 2018

Loading the required packages

Importing the case file and examining it

```
setwd("I:/DA/To Submit/Linear Regression Balance Prediction/")
cust_data <- fread("Cust_Database.csv")
str(cust_data)
```

```
## Classes 'data.table' and 'data.frame':  5000 obs. of  132 variables:
## $ custid      : chr  "3964-QJWTRG-NPN" "0648-AIPJSP-UVM" "5195-TLUDJE-HVO" "4459-VLPQUH-3OL" .
## $ region      : num  1 5 3 4 2 4 2 3 2 2 ...
## $ townsize    : num  2 5 4 3 2 4 5 4 3 2 ...
## $ gender      : num  1 0 1 0 0 0 1 1 1 0 ...
## $ age         : num  20 22 67 23 26 64 52 44 66 47 ...
## $ agecat      : num  2 2 6 2 3 5 5 4 6 4 ...
## $ birthmonth  : chr  "September" "May" "June" "May" ...
## $ ed          : num  15 17 14 16 16 17 14 16 12 11 ...
## $ edcat       : num  3 4 2 3 3 4 2 3 2 1 ...
## $ jobcat      : num  1 2 2 2 2 3 1 1 1 6 ...
## $ union       : num  1 0 0 0 0 0 0 0 0 0 ...
## $ employ      : num  0 0 16 0 1 22 10 11 15 19 ...
## $ empcat      : num  1 1 5 1 1 5 3 4 4 5 ...
## $ retire      : num  0 0 0 0 0 0 0 0 1 0 ...
## $ income      : num  31 15 35 20 23 107 77 97 16 84 ...
## $ lninc       : num  3.43 2.71 3.56 3 3.14 4.67 4.34 4.57 2.77 4.43 ...
## $ inccat      : num  2 1 2 1 1 4 4 4 1 4 ...
## $ debtinc     : num  11.1 18.6 9.9 5.7 1.7 5.6 1.9 14.4 2.6 4.1 ...
## $ creddebt    : num  1.2 1.22 0.93 0.02 0.21 1.06 0.5 5.95 0.1 1.77 ...
## $ lncreddebt  : num  0.18 0.2 -0.07 -3.78 -1.54 0.06 -0.69 1.78 -2.28 0.57 ...
## $ othdebt     : num  2.24 1.57 2.54 1.12 0.18 4.93 0.96 8.02 0.31 1.67 ...
## $ lnothdebt   : num  0.81 0.45 0.93 0.11 -1.74 1.6 -0.04 2.08 -1.16 0.52 ...
## $ default     : num  1 1 0 1 0 0 0 0 0 0 ...
## $ jobsat      : num  1 1 4 2 1 2 2 5 2 4 ...
## $ marital     : num  0 0 1 1 1 0 0 1 0 0 ...
## $ spoused     : num  -1 -1 13 18 13 -1 -1 15 -1 -1 ...
## $ spousedcat  : num  -1 -1 2 4 2 -1 -1 3 -1 -1 ...
## $ reside      : num  3 2 3 5 4 1 1 2 1 2 ...
## $ pets        : num  0 6 3 0 0 11 2 10 1 1 ...
## $ pets_cats   : num  0 0 2 0 0 1 0 0 1 1 ...
## $ pets_dogs   : num  0 0 1 0 0 1 2 2 0 0 ...
## $ pets_birds  : num  0 0 0 0 0 0 0 0 0 0 ...
## $ pets_reptiles : num  0 0 0 0 0 0 0 0 0 0 ...
## $ pets_small  : num  0 0 0 0 0 2 0 0 0 0 ...
## $ pets_saltfish : num  0 0 0 0 0 0 0 0 0 0 ...
## $ pets_freshfish : num  0 6 0 0 0 7 0 8 0 0 ...
## $ homeown     : num  0 1 1 1 0 1 0 1 1 1 ...
## $ hometype    : num  2 3 1 3 2 1 3 3 1 1 ...
## $ address     : num  0 2 30 3 3 31 21 20 21 19 ...
```

```

## $ addresscat      : num  1 1 5 2 2 5 4 4 4 4 ...
## $ cars            : num  2 2 3 3 1 0 2 1 1 4 ...
## $ carown          : num  1 1 1 1 0 -1 1 1 1 1 ...
## $ cartype         : num  0 1 1 1 1 -1 0 0 1 0 ...
## $ carvalue        : num  14.3 6.8 18.8 8.7 10.6 -1 25.6 55.5 8.6 41 ...
## $ carcatvalue     : num  1 1 1 1 1 -1 2 3 1 3 ...
## $ carbought       : num  0 0 0 0 0 -1 1 0 0 1 ...
## $ carbuy          : num  0 0 1 1 1 0 0 1 0 0 ...
## $ commute         : num  8 1 4 1 6 8 4 5 4 1 ...
## $ commutecat      : num  4 1 3 1 3 4 3 3 3 1 ...
## $ commutetime     : num  22 29 24 38 32 23 32 31 25 29 ...
## $ commutecar      : num  0 1 1 1 0 0 1 0 1 1 ...
## $ commutemotorcycle: num  1 0 0 0 0 0 0 0 1 1 ...
## $ commutecarpool  : num  1 0 1 0 0 0 0 0 0 0 ...
## $ commutebus      : num  0 1 1 0 0 0 1 0 1 0 ...
## $ commuterail     : num  0 0 1 0 0 1 0 1 1 0 ...
## $ commutepublic   : num  0 0 0 0 1 0 0 0 0 0 ...
## $ commutebike     : num  0 1 0 0 0 0 1 0 0 0 ...
## $ commutewalk     : num  1 0 0 0 1 1 1 0 0 0 ...
## $ commutenonmotor : num  0 1 0 0 0 0 0 0 0 0 ...
## $ telecommute     : num  0 1 0 0 0 0 0 0 0 0 ...
## $ reason          : num  9 9 2 9 9 9 9 2 9 9 ...
## $ polview         : num  6 4 5 3 4 4 4 6 3 3 ...
## $ polparty        : num  1 1 1 0 0 0 0 0 1 1 ...
## $ polcontrib      : num  0 0 0 0 0 0 0 0 1 1 ...
## $ vote            : num  1 0 0 0 0 0 0 1 1 1 ...
## $ card            : num  3 2 2 2 4 2 5 1 3 5 ...
## $ cardtype        : num  1 4 1 1 2 4 3 1 4 4 ...
## $ cardbenefit     : num  1 1 4 4 1 1 1 4 2 1 ...
## $ cardfee         : num  0 0 0 0 0 1 1 0 0 0 ...
## $ cardtenure      : num  2 4 35 5 8 18 3 25 26 2 ...
## $ cardtenurecat   : num  2 2 5 2 3 5 2 5 5 2 ...
## $ card2           : num  5 4 4 3 1 3 2 3 2 2 ...
## $ card2type       : num  3 1 1 2 3 3 3 1 4 2 ...
## $ card2benefit    : num  1 3 3 4 2 2 4 4 3 1 ...
## $ card2fee        : num  0 0 0 0 0 1 0 0 0 0 ...
## $ card2tenure     : num  3 4 25 5 9 9 2 20 17 2 ...
## $ card2tenurecat  : num  2 2 5 2 3 3 2 5 5 2 ...
## $ carditems       : num  5 5 9 17 8 11 20 6 12 11 ...
## $ cardspent       : num  81.7 42.6 184.2 341 255.1 ...
## $ card2items      : num  4 2 7 1 7 0 5 7 6 5 ...
## $ card2spent      : num  67.8 34.9 175.8 18.4 252.7 ...
## $ active          : num  0 1 0 1 1 0 0 0 1 1 ...
## $ bfast           : num  3 1 3 1 3 3 2 3 3 3 ...
## $ tenure          : num  5 39 65 36 21 28 15 46 53 3 ...
## $ churn           : num  1 0 0 0 0 0 0 0 0 1 ...
## $ longmon         : num  6.5 8.9 28.4 6 3.05 ...
## $ lnlongmon       : num  1.87 2.19 3.35 1.79 1.12 2.09 1.34 2.7 3.05 1.29 ...
## $ longten         : num  34.4 330.6 1858.3 199.4 74.1 ...
## $ lnlongten       : num  3.54 5.8 7.53 5.3 4.31 5.58 3.8 6.42 6.98 3 ...
## $ tollfree        : num  1 0 0 0 1 1 0 1 0 0 ...
## $ tollmon         : num  29 0 0 0 16.5 ...
## $ lntollmon       : num  3.37 NA NA NA 2.8 3.29 NA 3.18 NA NA ...
## $ tollten         : num  161 0 0 0 388 ...

```

```
## $ lntollten      : num  5.08 NA NA NA 5.96 6.59 NA 7.01 NA NA ...
## $ equip         : num  1 1 0 0 0 1 0 0 0 0 ...
## $ equipmon      : num  29.5 54.9 0 0 0 ...
## $ lnequipmon    : num  3.38 4 NA NA NA 3.57 NA NA NA NA ...
## $ equipten      : num  126 1975 0 0 0 ...
## $ lnequipten    : num  4.84 7.59 NA NA NA 6.88 NA NA NA NA ...
## [list output truncated]
## - attr(*, ".internal.selfref")=<externalptr>

cust_ <- cust_data
```

Making necessary changes to variable types

```
cust_$region <- factor(cust_data$region, levels = c(1,2,3,4,5), labels = c("zone 1", "zone 2", "zone 3", "zone 4", "zone 5"))
cust_$townsize <- factor(cust_data$townsize, levels = c(1,2,3,4,5), labels = c("> 250,000", "50,000-249,999", "25,000-49,999", "10,000-24,999", "0-9,999"))
cust_$gender <- factor(cust_data$gender, levels = c(0,1), labels = c("Male", "Female"))
cust_$agecat <- factor(cust_data$agecat, levels = c(1,2,3,4,5,6,9), labels = c("<18", "18-24", "25-34", "35-49", "50-64", "65-74", "75-84", "85-94", "95-104"))
cust_$birthmonth <- factor(cust_data$birthmonth, levels = c("April", "August", "December", "February", "January", "July", "June", "March", "May", "November", "October", "September"), labels = c("April", "August", "December", "February", "January", "July", "June", "March", "May", "November", "October", "September"))
cust_$edcat <- ordered(cust_data$edcat, levels = c(1,2,3,4,5), labels = c("Did not complete high school", "High school graduate", "Some college", "Bachelor's degree", "Postgraduate"))
cust_$jobcat <- factor(cust_data$jobcat, levels = c(1,2,3,4,5,6), labels = c("Managerial and Professional", "Technical", "Sales", "Service", "Craft", "Unemployed"))
cust_$jobcat <- factor(cust_data$union, levels = c(0,1), labels = c("No", "Yes"))
cust_$employ <- as.factor(cust_data$employ)
cust_$empcat <- factor(cust_data$empcat, levels = c(1,2,3,4,5), labels = c("Less than 2", "2 to 5", "6 to 10", "11 to 20", "21 or more"))
cust_$retire <- factor(cust_data$retire, levels = c(0,1), labels = c("No", "Yes"))
cust_$inccat <- ordered(cust_data$inccat, levels = c(1,2,3,4,5), labels = c("Under $25", "$25 - $49", "$50 - $74", "$75 - $99", "$100 or more"))
cust_$default <- factor(cust_data$default, levels = c(0,1), labels = c("No", "Yes"))
cust_$jobsat <- ordered(cust_data$jobsat, levels = c(1,2,3,4,5), labels = c("Highly dissatisfied", "Somewhat dissatisfied", "Satisfied", "Very satisfied", "Extremely satisfied"))
cust_$marital <- factor(cust_data$marital, levels = c(0,1), labels = c("Unmarried", "Married"))
cust_$spousedcat <- factor(cust_data$spousedcat, levels = c(-1,1,2,3,4,5), labels = c("Not married", "Did not marry", "Married", "Widowed", "Divorced"))
cust_$homeown <- factor(cust_data$homeown, levels = c(0,1), labels = c("Rent", "Own"))
cust_$hometype <- factor(cust_data$hometype, levels = c(1,2,3,4), labels = c("Single-family", "Multiple-family", "Mobile home", "Other"))
cust_$address <- as.factor(cust_data$address)
cust_$addresscat <- ordered(cust_data$addresscat, levels = c(1,2,3,4,5), labels = c("Less than 3", "4 to 7", "8 to 11", "12 to 15", "16 or more"))
cust_$cars <- as.ordered(cust_data$cars)
cust_$carown <- factor(cust_data$carown, levels = c(-1,0,1), labels = c("N/A", "Lease", "Own"))
cust_$cartype <- factor(cust_data$cartype, levels = c(-1,0,1), labels = c("N/A", "Domestic", "Import"))
cust_$carcatvalue <- ordered(cust_data$carcatvalue, levels = c(-1,1,2,3), labels = c("N/A", "Economy", "Standard", "Premium", "Luxury"))
cust_$carbought <- factor(cust_data$carbought, levels = c(-1,0,1), labels = c("N/A", "No", "Yes"))
cust_$carbuy <- factor(cust_data$carbuy, levels = c(0,1), labels = c("No", "Yes"))
cust_$commute <- factor(cust_data$commute, levels = c(1,2,3,4,5,6,7,8,9,10), labels = c("Car", "Motorcycle", "Bicycle", "Walk", "Public transit", "Taxi", "Ride share", "Other"))
cust_$commutecat <- factor(cust_data$commutecat, levels = c(1,2,3,4,5), labels = c("Single occupancy", "Multiple occupancy", "Solo", "Partner", "Family"))
cust_$commutecar <- factor(cust_data$commutecar, levels = c(0,1), labels = c("No", "Yes"))
cust_$commutemotorcycle <- factor(cust_data$commutemotorcycle, levels = c(0,1), labels = c("No", "Yes"))
cust_$commutecarpool <- factor(cust_data$commutecarpool, levels = c(0,1), labels = c("No", "Yes"))
cust_$commutebus <- factor(cust_data$commutebus, levels = c(0,1), labels = c("No", "Yes"))
cust_$commuterail <- factor(cust_data$commuterail, levels = c(0,1), labels = c("No", "Yes"))
cust_$commutepublic <- factor(cust_data$commutepublic, levels = c(0,1), labels = c("No", "Yes"))
cust_$commutebike <- factor(cust_data$commutebike, levels = c(0,1), labels = c("No", "Yes"))
cust_$commutewalk <- factor(cust_data$commutewalk, levels = c(0,1), labels = c("No", "Yes"))
cust_$commutenonmotor <- factor(cust_data$commutenonmotor, levels = c(0,1), labels = c("No", "Yes"))
cust_$telecommute <- factor(cust_data$telecommute, levels = c(0,1), labels = c("No", "Yes"))
cust_$reason <- factor(cust_data$reason, levels = c(1,2,3,4,8,9), labels = c("Prices", "Convenience", "Service", "Safety", "Other"))
cust_$polview <- factor(cust_data$polview, levels = c(1,2,3,4,5,6,7), labels = c("Extremely liberal", "Liberal", "Moderate liberal", "Moderate conservative", "Conservative", "Extremely conservative", "Other"))
cust_$polparty <- factor(cust_data$polparty, levels = c(0,1), labels = c("No", "Yes"))
```

```

cust_$polcontrib <- factor(cust_$polcontrib, levels = c(0,1), labels = c("No","Yes"))
cust_$vote <- factor(cust_$vote, levels = c(0,1), labels = c("No","Yes"))
cust_$card <- factor(cust_$card, levels = c(1,2,3,4,5), labels = c("American Express","Visa","Mastercard","Discover","Other"))
cust_$cardtype <- factor(cust_$cardtype, levels = c(1,2,3,4), labels = c("None","Gold","Platinum","Other"))
cust_$cardbenefit <- factor(cust_$cardbenefit, levels = c(1,2,3,4), labels = c("None","Cash back","Airline miles","Other"))
cust_$cardfee <- factor(cust_$cardfee, levels = c(0,1), labels = c("No","Yes"))
cust_$cardtenure <- ordered(cust_$cardtenure)
cust_$cardtenurecat <- ordered(cust_$cardtenure, levels= c(1,2,3,4,5), labels= c("Less than 2","2 to 5","6 to 10","11 to 15","16 to 20"))
cust_$card2 <- factor(cust_$card2, levels = c(1,2,3,4,5), labels = c("American Express","Visa","Mastercard","Discover","Other"))
cust_$card2type <- factor(cust_$card2type, levels = c(1,2,3,4), labels = c("None","Gold","Platinum","Other"))
cust_$card2benefit <- factor(cust_$card2benefit, levels = c(1,2,3,4), labels = c("None","Cash back","Airline miles","Other"))
cust_$card2fee <- factor(cust_$card2fee, levels = c(0,1), labels = c("No","Yes"))
cust_$card2tenure <- ordered(cust_$card2tenure)
cust_$card2tenurecat <- ordered(cust_$card2tenure, levels= c(1,2,3,4,5), labels= c("Less than 2","2 to 5","6 to 10","11 to 15","16 to 20"))
cust_$active <- factor(cust_$active, levels = c(0,1), labels = c("No","Yes"))
cust_$bfast <- factor(cust_$bfast, levels = c(1,2,3), labels = c("Energy bar","Oatmeal","Cereal"))
cust_$churn <- factor(cust_$churn, levels = c(0,1), labels = c("No","Yes"))
cust_$tollfree <- factor(cust_$tollfree, levels = c(0,1), labels = c("No","Yes"))
cust_$equip <- factor(cust_$equip, levels = c(0,1), labels = c("No","Yes"))
cust_$callcard <- factor(cust_$callcard, levels = c(0,1), labels = c("No","Yes"))
cust_$wireless <- factor(cust_$wireless, levels = c(0,1), labels = c("No","Yes"))
cust_$multiline <- factor(cust_$multiline, levels = c(0,1), labels = c("No","Yes"))
cust_$voice <- factor(cust_$voice, levels = c(0,1), labels = c("No","Yes"))
cust_$pager <- factor(cust_$pager, levels = c(0,1), labels = c("No","Yes"))
cust_$internet <- factor(cust_$internet, levels = c(0,1,2,3,4), labels = c("None", "Dia-up","DSL","Cable","Other"))
cust_$callid <- factor(cust_$callid, levels = c(0,1), labels = c("No","Yes"))
cust_$callwait <- factor(cust_$callwait, levels = c(0,1), labels = c("No","Yes"))
cust_$forward <- factor(cust_$forward, levels = c(0,1), labels = c("No","Yes"))
cust_$confer <- factor(cust_$confer, levels = c(0,1), labels = c("No","Yes"))
cust_$ebill <- factor(cust_$ebill, levels = c(0,1), labels = c("No","Yes"))
cust_$owntv <- factor(cust_$owntv, levels = c(0,1), labels = c("No","Yes"))
cust_$ownvcr <- factor(cust_$ownvcr, levels = c(0,1), labels = c("No","Yes"))
cust_$owndvd <- factor(cust_$owndvd, levels = c(0,1), labels = c("No","Yes"))
cust_$owncd <- factor(cust_$owncd, levels = c(0,1), labels = c("No","Yes"))
cust_$ownpda <- factor(cust_$ownpda, levels = c(0,1), labels = c("No","Yes"))
cust_$ownpc <- factor(cust_$ownpc, levels = c(0,1), labels = c("No","Yes"))
cust_$ownpod <- factor(cust_$ownpod, levels = c(0,1), labels = c("No","Yes"))
cust_$owngame <- factor(cust_$owngame, levels = c(0,1), labels = c("No","Yes"))
cust_$ownfax <- factor(cust_$ownfax, levels = c(0,1), labels = c("No","Yes"))
cust_$news <- factor(cust_$news, levels = c(0,1), labels = c("No","Yes"))
cust_$response_01 <- factor(cust_$response_01, levels = c(0,1), labels = c("No","Yes"))
cust_$response_02 <- factor(cust_$response_02, levels = c(0,1), labels = c("No","Yes"))
cust_$response_03 <- factor(cust_$response_03, levels = c(0,1), labels = c("No","Yes"))

```

A user defined function to see about the data

```

about_nums <- function(x){
  n = length(x)
  nmiss = sum(is.na(x))
  nmiss_pct = (mean(is.na(x)))*100
  sum = sum(x, na.rm=T)
  mean = mean(x, na.rm=T)
}

```

```

median = quantile(x, p=0.5, na.rm=T)
std = sd(x, na.rm=T)
var = var(x, na.rm=T)
range = max(x, na.rm=T)-min(x, na.rm=T)
pctl = quantile(x, p=c(0, 0.01, 0.05,0.1,0.25,0.5, 0.75,0.9,0.95,0.99,1), na.rm=T)
return(c(N=n, Nmiss =nmiss, Nmiss_pct = nmiss_pct, sum=sum, avg=mean, meidan=median, std=std, var=var

}

about_cats <- function(x){

  n = length(x)
  nmiss = sum(is.na(x))
  nmiss_pct = (mean(is.na(x)))*100
  return(c(N=n, Nmiss =nmiss, Nmiss_pct = nmiss_pct))

}

```

Taking numerics and non-numerics as two subsets

```

numerics <- names(cust_)[sapply(cust_, is.numeric)]
# cust_nums <- cust_[,..numerics,] -----> creates subset of numeric vars

non_nums <- as.data.frame(names(cust_))
nums <- as.data.frame(numerics)
rest <- non_nums[!non_nums$`names(cust_)`%in%nums$numerics,]
rest <- as.vector(rest)
# non_nums <- cust_[,..rest,] -----> creates subset of non-nums

```

Examining through the variables

Numeric

```

nums <- as.data.frame(t(sapply(cust_[,..numerics,], about_nums)))
kep <- row.names(nums[nums$Nmiss_pct<50,]) # ----- removing variables with missing more than 50% m
numerics_cust <- cust_[,..kep]
# For the rest of the variables with missing, the mean value is inserted
miss_treat_num = function(x){
  x[is.na(x)] = mean(x,na.rm=T) # replace missings with mean
  return(x)
}
numerics_cust <- data.table(apply(numerics_cust,2, FUN = miss_treat_num))
nums <- as.data.frame(t(sapply(numerics_cust, about_nums)))
fwrite(nums,"num_outliers.csv")

```

Capping outliers in the data

Capping with 95 percentile

```

outlier_treat_95 <- function(x){
  UC1 = quantile(x, p=0.95,na.rm=T)
  LC1 = quantile(x, p=0.05,na.rm=T)

```

```

  x=ifelse(x>UC1, UC1, x)
  x=ifelse(x<LC1, LC1, x)
  return(x)
}

cap95 <- numerics_cust[,c(1,21)]
cap95 <- data.table(apply(cap95,2, FUN = outlier_treat_95))

```

Capping with 99 percentile value

```

outlier_treat_99 <- function(x){
  UC1 = quantile(x, p=0.99,na.rm=T)
  LC1 = quantile(x, p=0.01,na.rm=T)

  x=ifelse(x>UC1, UC1, x)
  x=ifelse(x<LC1, LC1, x)
  return(x)
}

cap99 <- numerics_cust[,c(-1,-21)]
cap99 <- data.table(apply(cap99,2, FUN = outlier_treat_99))

numerics_cust <- cbind(cap95, cap99)

```

Categorical

```

cats <- as.data.frame(t(sapply(cust_[,..numerics,], about_cats)))

cat_cust <- cust_[,..numerics,]
cat_cust$cardtenurecat <- NULL
cat_cust$card2tenurecat <- NULL

cust_final <- cbind(numerics_cust, cat_cust)
cust_final$total_spent <- cust_final$cardspent + cust_final$card2spent

```

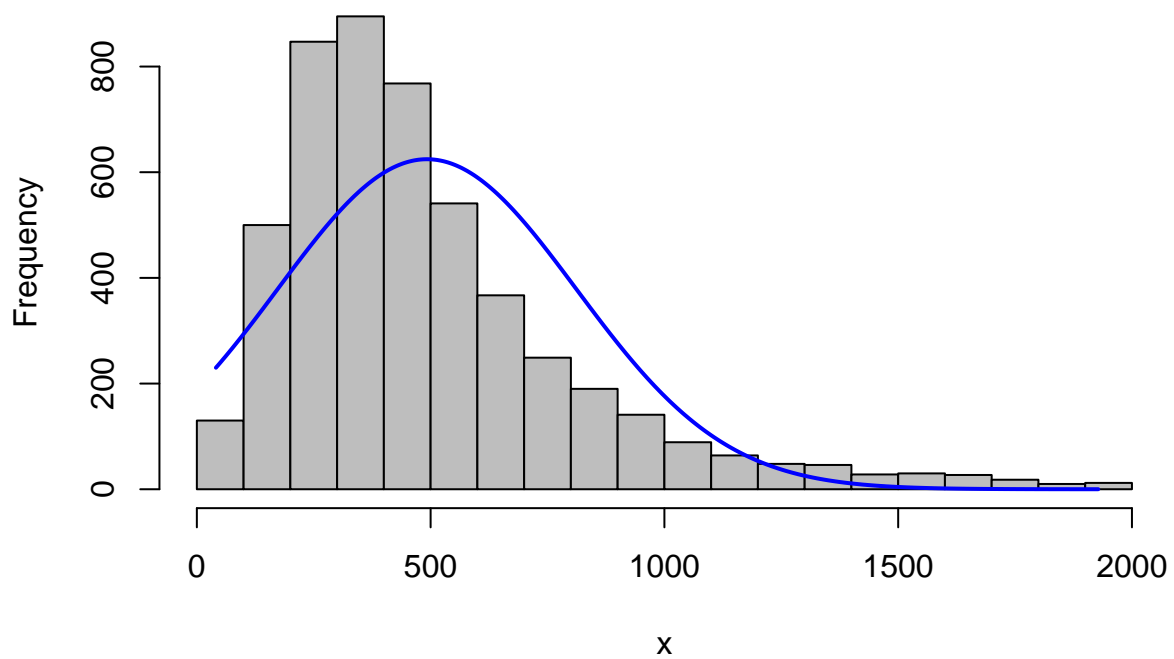
Checking regression assumptions

Normality of Y variable

```

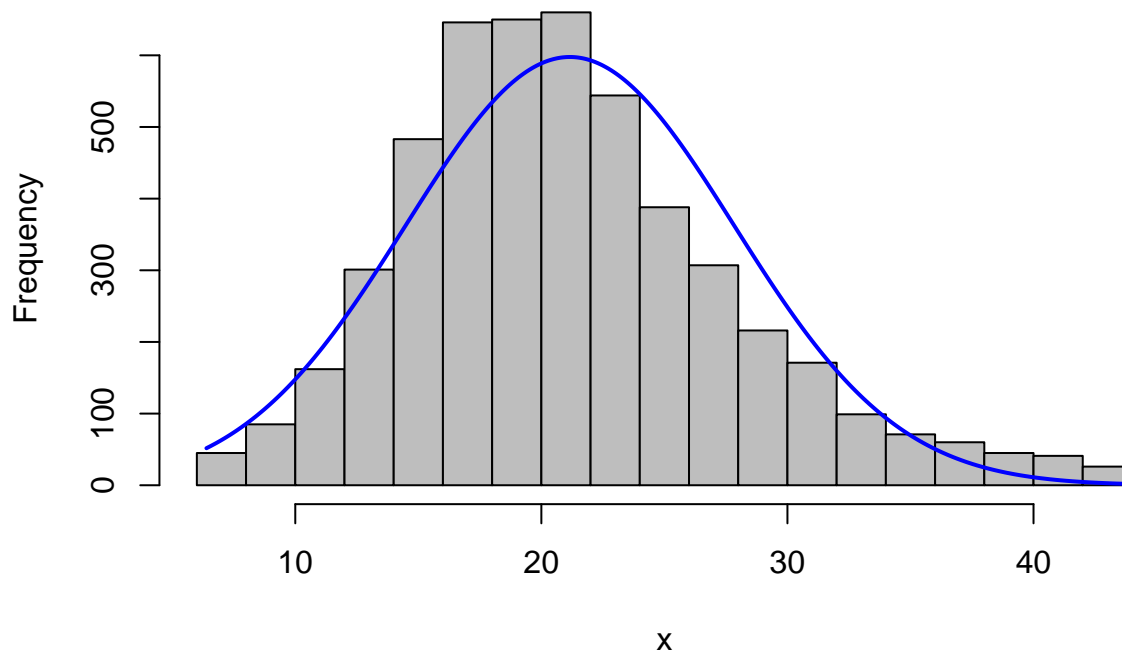
plotNormalHistogram(cust_final$total_spent)

```



```
shapiro.test(cust_final$total_spent)
```

```
##  
##  Shapiro-Wilk normality test  
##  
## data:  cust_final$total_spent  
## W = 0.87136, p-value < 0.000000000000000022  
  
# This is not normal hence it is transformed  
cust_final$total_spent_sqrt <- sqrt(cust_final$total_spent)  
plotNormalHistogram(cust_final$total_spent_sqrt)
```



```
cust_final$total_spent_sqrt <- sqrt(cust_final$total_spent)
```

This shows a more normal distribution, thus this will be used as Y

Checking if Y variables and X Variables are correlated

```
numerics_cust <- cbind(numerics_cust, total_spent_sqrt=cust_final$total_spent_sqrt, total_spent = cust_final$total_spent)
cormat <- as.data.frame(cor(numerics_cust))
fwrite(cormat, "cormat.csv", row.names = T)
remove_ <- c("age", "union", "debtinc", "spoused", "reside", "pets", "pets_cats", "pets_dogs", "pets_birds",
             "pets_reptiles", "pets_small", "pets_saltfish", "pets_freshfish", "commutetime", "tenure", "longten",
             "lnlongmon", "longten", "lnlongten", "tollmon", "equipmon", "equipten", "cardmon", "lncardmon",
             "cardten", "lncardten", "wiremon", "hourstv")
# removing all numeric variables that are not correlated with total_spent
cust_final <- cust_final[, -..remove_,]
# removing variables with high inter-item correlation with 0.6 as limit
remove_ <- c("carvalue", "income", "creddebt", "lnothdebt", "card2items")
cust_final <- cust_final[, -..remove_,]
```

Checking the relationship of categorical X variables with Y variable

```
Anov <- function(x){
  summary(aov(cust_final$total_spent~x))
}
```



```
cat_cust$custid <- NULL
apply(cat_cust, 2, FUN = Anov)
```

```
## $region
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           4   1054636   263659   2.588  0.035 *
## Residuals  4995  508790498   101860
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $townsize
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           4    136780    34195   0.335  0.855
## Residuals  4993  509622803   102067
## 2 observations deleted due to missingness
##
## $gender
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1   3068393  3068393   30.26 0.0000000396 ***
## Residuals  4998  506776741   101396
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $agecat
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           4  14551607  3637902   36.69 <0.0000000000000002 ***
## Residuals  4995  495293527    99158
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $birthmonth
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x          11    439019    39911   0.391  0.96
## Residuals  4988  509406116   102126
##
## $edcat
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           4   5050828  1262707   12.49 0.000000000409 ***
## Residuals  4995  504794307   101060
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $jobcat
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1    70766    70766   0.694  0.405
## Residuals  4998  509774368   101996
##
## $employ
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x          51  13336411   261498   2.606 0.00000000446 ***
## Residuals  4948  496508723   100345
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```

## $empcat
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           4   7045584 1761396    17.5 0.0000000000000286 ***
## Residuals 4995 502799550 100661
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $retire
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1  14674020 14674020   148.1 <0.0000000000000002 ***
## Residuals 4998 495171114   99074
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $inccat
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           4   76130691 19032673   219.2 <0.0000000000000002 ***
## Residuals 4995 433714443   86830
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $default
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1     38194   38194   0.374  0.541
## Residuals 4998 509806941 102002
##
## $jobsat
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           4   3596431  899108    8.871 0.000000391 ***
## Residuals 4995 506248704 101351
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $marital
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1     94361   94361   0.925  0.336
## Residuals 4998 509750773 101991
##
## $spousedcat
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           5   1528394  305679    3.003 0.0104 *
## Residuals 4994 508316740 101785
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $homeown
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1   2673048 2673048   26.34 0.000000297 ***
## Residuals 4998 507172086 101475
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $hometype
##           Df      Sum Sq Mean Sq F value      Pr(>F)

```

```

## x          3    2057899  685966    6.749 0.000154 ***
## Residuals  4996 507787235  101639
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $address
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           56   10884689   194369    1.926 0.0000453 ***
## Residuals  4943 498960445   100943
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $addresscat
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           4    6843762  1710940   16.99 0.0000000000000759 ***
## Residuals  4995 503001373   100701
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $cars
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           8    677094    84637    0.83  0.576
## Residuals  4991 509168041   102017
##
## $carown
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           2   10107155  5053578   50.53 <0.0000000000000002 ***
## Residuals  4997 499737979   100008
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $cartype
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           2    391449   195724    1.92  0.147
## Residuals  4997 509453686   101952
##
## $carcatvalue
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           3   57143454  19047818   210.2 <0.0000000000000002 ***
## Residuals  4996 452701680    90613
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $carbought
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           2    354037   177018    1.736 0.176
## Residuals  4997 509491098   101959
##
## $carbuy
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           1    117182   117182    1.149 0.284
## Residuals  4998 509727953   101986
##
## $commute

```

```

##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           9      949548   105505    1.035   0.409
## Residuals  4990  508895587   101983
##
## $commutecat
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           4      303267    75817    0.743   0.562
## Residuals  4995  509541868   102010
##
## $commutecar
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      41137    41137    0.403   0.525
## Residuals  4998  509803998   102002
##
## $commutemotorcycle
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      230742   230742    2.263   0.133
## Residuals  4998  509614393   101964
##
## $commutecarpool
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      18970    18970    0.186   0.666
## Residuals  4998  509826165   102006
##
## $commutebus
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      63297    63297    0.621   0.431
## Residuals  4998  509781837   101997
##
## $commuterail
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      22512    22512    0.221   0.639
## Residuals  4998  509822622   102005
##
## $commutepublic
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1         30         30      0 0.986
## Residuals  4998  509845105   102010
##
## $commutebike
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      477132   477132    4.682 0.0305 *
## Residuals  4998  509368002   101914
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $commutewalk
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      10699    10699    0.105   0.746
## Residuals  4998  509834435   102008
##
## $commutenonmotor
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      69678    69678    0.683   0.409

```

```

## Residuals    4998 509775457 101996
##
## $telecommute
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      34691   34691    0.34   0.56
## Residuals    4998 509810444 102003
##
## $reason
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           4  14817637 3704409   37.38 <0.0000000000000002 ***
## Residuals    4995 495027497   99105
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $polview
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           6  1209432  201572   1.979 0.0651 .
## Residuals    4993 508635703 101870
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $polparty
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      41327   41327   0.405 0.524
## Residuals    4998 509803807 102002
##
## $polcontrib
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      494343  494343   4.851 0.0277 *
## Residuals    4998 509350791 101911
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $vote
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1  2170590 2170590   21.37 0.00000388 ***
## Residuals    4998 507674545 101576
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $card
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           4  72491796 18122949    207 <0.0000000000000002 ***
## Residuals    4995 437353338   87558
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $cardtype
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           3   129747   43249   0.424 0.736
## Residuals    4996 509715387 102025
##
## $cardbenefit
##           Df      Sum Sq Mean Sq F value Pr(>F)

```

```

## x          3      546128  182043   1.786  0.148
## Residuals  4996 509299006  101941
##
## $cardfee
##          Df      Sum Sq Mean Sq F value Pr(>F)
## x          1      13579   13579   0.133  0.715
## Residuals  4998 509831555  102007
##
## $cardtenure
##          Df      Sum Sq Mean Sq F value   Pr(>F)
## x          40     7780859  194521   1.921 0.000443 ***
## Residuals  4959 502064275  101243
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $card2
##          Df      Sum Sq Mean Sq F value          Pr(>F)
## x          4     15378634  3844659   38.84 <0.0000000000000002 ***
## Residuals  4995 494466500   98992
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $card2type
##          Df      Sum Sq Mean Sq F value Pr(>F)
## x          3       62545   20848   0.204  0.893
## Residuals  4996 509782589  102038
##
## $card2benefit
##          Df      Sum Sq Mean Sq F value Pr(>F)
## x          3      242830   80943   0.794  0.497
## Residuals  4996 509602304  102002
##
## $card2fee
##          Df      Sum Sq Mean Sq F value Pr(>F)
## x          1      498034   498034   4.887 0.0271 *
## Residuals  4998 509347100  101910
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $card2tenure
##          Df      Sum Sq Mean Sq F value   Pr(>F)
## x          30     7616630  253888   2.512 0.0000101 ***
## Residuals  4969 502228504  101072
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $active
##          Df      Sum Sq Mean Sq F value Pr(>F)
## x          1       51818   51818   0.508  0.476
## Residuals  4998 509793316  101999
##
## $bfast
##          Df      Sum Sq Mean Sq F value Pr(>F)
## x          2      551504  275752   2.706 0.0669 .

```

```

## Residuals    4997 509293631  101920
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $churn
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1      50479   50479    0.495  0.482
## Residuals   4998 509794656  102000
##
## $tollfree
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1    1730013 1730013    17.02 0.0000376 ***
## Residuals   4998 508115121  101664
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $equip
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1    1347603 1347603    13.25 0.000276 ***
## Residuals   4998 508497531  101740
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $callcard
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1     436712   436712    4.285 0.0385 *
## Residuals   4998 509408422  101922
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $wireless
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1    2219718 2219718    21.86 0.00000302 ***
## Residuals   4998 507625416  101566
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $multline
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1    1200261 1200261    11.79 0.000599 ***
## Residuals   4998 508644873  101770
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $voice
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1     583189   583189    5.724 0.0168 *
## Residuals   4998 509261945  101893
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $pager
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1    1540683 1540683    15.15 0.000101 ***

```

```

## Residuals    4998 508304451  101702
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $internet
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           4   2945817   736454    7.257 0.000008 ***
## Residuals   4995 506899317   101481
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $callid
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           1   1559884  1559884   15.34 0.0000911 ***
## Residuals   4998 508285250   101698
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $callwait
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           1   1707810  1707810   16.8 0.0000422 ***
## Residuals   4998 508137324   101668
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $forward
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           1   1490594  1490594   14.65 0.000131 ***
## Residuals   4998 508354540   101712
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $confer
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           1   1732684  1732684   17.04 0.0000371 ***
## Residuals   4998 508112451   101663
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $ebill
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           1    453338   453338    4.448  0.035 *
## Residuals   4998 509391796   101919
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $owntv
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           1   2594300  2594300   25.56 0.000000444 ***
## Residuals   4998 507250834   101491
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $ownvcr

```



```

##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1    9206679 9206679    91.91 <0.0000000000000002 ***
## Residuals  4998 500638455  100168
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $owndvd
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1    9843802 9843802    98.4 <0.0000000000000002 ***
## Residuals  4998 500001333  100040
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $owncd
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1    7543624 7543624    75.06 <0.0000000000000002 ***
## Residuals  4998 502301510  100501
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $ownpda
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1    2514947 2514947    24.78 0.0000000666 ***
## Residuals  4998 507330187  101507
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $ownpc
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1    1311225 1311225    12.89 0.000334 ***
## Residuals  4998 508533909  101747
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $ownipod
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1    494879  494879    4.856 0.0276 *
## Residuals  4998 509350255  101911
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $owngame
##           Df      Sum Sq Mean Sq F value Pr(>F)
## x           1    362131  362131    3.552 0.0595 .
## Residuals  4998 509483003  101937
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $ownfax
##           Df      Sum Sq Mean Sq F value      Pr(>F)
## x           1    1772441 1772441    17.44 0.0000302 ***
## Residuals  4998 508072693  101655
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
##
## $news
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           1      841780   841780     8.266 0.00406 **
## Residuals  4998  509003354   101841
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $response_01
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           1      28651    28651     0.281  0.596
## Residuals  4998  509816483   102004
##
## $response_02
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           1      258071   258071     2.531  0.112
## Residuals  4998  509587063   101958
##
## $response_03
##           Df      Sum Sq Mean Sq F value    Pr(>F)
## x           1     1358424  1358424    13.35 0.000261 ***
## Residuals  4998  508486711   101738
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
# Categories that are insignificant are removed except for those that needed to be kept in relation to
remove_ <- c("townsize","birthmonth","jobcat","default","marital","cars","carbought","carbuy","commute"
            "commutecar","commutemotorcycle","commutecarpool","commutebus","commuterail","commutepublic"
            "commutewalk","commutenonmotor","telecommute","polparty","response_01","response_02")
cust_final <- cust_final[,-remove_,]
```

Creating dummy variables and preparing data for building the model

```
cust_final$custid <- NULL
ordered <- names(cust_final)[sapply(cust_final, is.ordered)]
cust_ordered <- cust_final[,..ordered,]
cust_final <- cust_final[,-..ordered,]
factor <- names(cust_final)[sapply(cust_final, is.factor)]
dd <- dummy_cols(cust_final, remove_first_dummy = TRUE)
cust_final <- dd[,..factor,]
cust_final <- cbind(cust_final,cust_ordered)
```

Building the Regression model

Taking samples

```
set.seed(654)
samp <- sample(1:nrow(cust_final),size = floor(nrow(cust_final)*0.7))
Dev <- cust_final[samp,]
Test <- cust_final[-samp,]

fit <- lm(total_spent_sqrt~.,data = Dev)
summary(fit)
```

```
##
## Call:
## lm(formula = total_spent_sqrt ~ ., data = Dev)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6.4751 -0.5459  0.2084  0.7768  2.5887
##
## Coefficients: (11 not defined because of singularities)
##              Estimate Std. Error t value
## (Intercept)    6.91333713  0.69649351   9.926
## ed            -0.00140350  0.02745284  -0.051
## lninc         0.69831765  0.12968129   5.385
## lncreddebt     0.02072706  0.02219918   0.934
## othdebt       -0.00435045  0.00732124  -0.594
## carditems     0.21583534  0.00815976  26.451
## cardspent     0.01727199  0.00016413 105.236
## card2spent    0.02166340  0.00021350 101.466
## tollten       0.00002357  0.00004415   0.534
## wireten       0.00004175  0.00004369   0.955
## total_spent    NA           NA        NA
## `region_zone 5` -0.01199707  0.06720150  -0.179
## `region_zone 3` -0.05912040  0.06687519  -0.884
## `region_zone 4` -0.03102811  0.06730258  -0.461
## `region_zone 2` -0.00462108  0.06736190  -0.069
## gender_Male     0.01607822  0.04265714   0.377
## `agecat_>65`    0.30952765  0.18588498   1.665
## `agecat_25-34`  0.01098643  0.13450969   0.082
## `agecat_50-64`  0.20159468  0.17112258   1.178
## `agecat_35-49`  0.22167723  0.15815212   1.402
## employ_16       0.13608612  0.19637449   0.693
## employ_1       -0.07360934  0.10751250  -0.685
## employ_22      -0.21872293  0.27169424  -0.805
## employ_10      -0.24871889  0.16408343  -1.516
## employ_11      -0.19072643  0.16163823  -1.180
## employ_15      -0.15733291  0.18356144  -0.857
## employ_19      -0.01923199  0.20499162  -0.094
## employ_8       -0.32437281  0.15598327  -2.080
## employ_4       -0.19700026  0.13344517  -1.476
## employ_12      -0.11113669  0.17881030  -0.622
## employ_3       -0.11442906  0.12859232  -0.890
## employ_27      -0.09195162  0.28106075  -0.327
## employ_31      -0.06843752  0.28908829  -0.237
## employ_24      -0.40904652  0.27423092  -1.492
## employ_29      -0.02915824  0.30029734  -0.097
## employ_2       -0.18443642  0.11999283  -1.537
## employ_18      -0.30479053  0.21514811  -1.417
## employ_5       -0.31111477  0.13953403  -2.230
## employ_28      -0.32166996  0.32738624  -0.983
## employ_26      -0.28970764  0.25924798  -1.117
## employ_23      -0.05837279  0.23783918  -0.245
## employ_13       0.08633709  0.17891518   0.483
## employ_17      -0.12162279  0.19590012  -0.621
## employ_30      -0.26851161  0.28863370  -0.930
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## employ_14	-0.32357015	0.19616578	-1.649
## employ_6	-0.09682807	0.14317633	-0.676
## employ_36	-0.09748749	0.39349958	-0.248
## employ_7	-0.02732906	0.15270504	-0.179
## employ_9	-0.31214508	0.15948150	-1.957
## employ_21	0.11025111	0.23443307	0.470
## employ_20	-0.32042492	0.20989408	-1.527
## employ_34	-0.18393779	0.30485298	-0.603
## employ_35	-0.35755690	0.41717182	-0.857
## employ_33	0.25730651	0.34459653	0.747
## employ_25	0.20487864	0.27201180	0.753
## employ_39	0.11810635	0.40181513	0.294
## employ_45	-1.49377124	0.93903219	-1.591
## employ_32	-0.09263997	0.31905724	-0.290
## employ_40	0.29390447	0.64758249	0.454
## employ_37	-0.29185086	0.43319791	-0.674
## employ_48	0.12053092	1.25252903	0.096
## employ_38	-0.10225568	0.38256365	-0.267
## employ_46	-0.13090572	1.28211748	-0.102
## employ_43	0.11452598	0.74317357	0.154
## employ_47	0.15455844	1.26495485	0.122
## employ_41	2.03681933	1.26722011	1.607
## employ_42	0.58745218	0.58633973	1.002
## employ_49	-0.04278096	1.26978033	-0.034
## employ_44	0.64427027	0.59314132	1.086
## employ_52	-0.77639107	1.32660798	-0.585
## employ_51	1.12080188	1.26486671	0.886
## `empcat_More than 15`	NA	NA	NA
## `empcat_6 to 10`	NA	NA	NA
## `empcat_11 to 15`	NA	NA	NA
## `empcat_2 to 5`	NA	NA	NA
## retire_Yes	-0.13076625	0.11158786	-1.172
## `spousedcat_High school degree`	-0.01542996	0.06318898	-0.244
## `spousedcat_College degree`	0.08686225	0.08385085	1.036
## `spousedcat_Some college`	0.07511438	0.07425164	1.012
## `spousedcat_Did not complete high school`	-0.05906807	0.07220504	-0.818
## `spousedcat_Post-undergraduate degree`	-0.06612115	0.15717449	-0.421
## homeown_Own	-0.08221209	0.06575953	-1.250
## `hometype_Condominium/Townhouse`	0.04096802	0.08096860	0.506
## `hometype_Single-family`	0.08338028	0.06948214	1.200
## `hometype_Mobile Home`	0.07957723	0.10888896	0.731
## address_2	0.10200118	0.17936558	0.569
## address_30	0.16729462	0.26494662	0.631
## address_3	-0.14223948	0.19713677	-0.722
## address_31	-0.24830995	0.26641323	-0.932
## address_21	-0.34830969	0.24134252	-1.443
## address_20	-0.42550647	0.24837483	-1.713
## address_19	-0.19324641	0.25062460	-0.771
## address_14	0.09134708	0.23159017	0.394
## address_5	-0.22844201	0.21136591	-1.081
## address_9	0.06770719	0.22992286	0.294
## address_32	0.14293497	0.27380554	0.522
## address_29	-0.33736660	0.26791205	-1.259
## address_8	-0.18724233	0.22138681	-0.846

## address_12	-0.25785390	0.22447382	-1.149
## address_10	-0.15827347	0.22914394	-0.691
## address_38	-0.14594241	0.31043023	-0.470
## address_4	-0.04048651	0.20223667	-0.200
## address_57	0.41442638	0.76477420	0.542
## address_16	-0.03713520	0.23887844	-0.155
## address_27	-0.30492604	0.25956912	-1.175
## address_6	0.12146786	0.21844693	0.556
## address_35	-0.06375698	0.30499429	-0.209
## address_25	-0.26161880	0.25492123	-1.026
## address_36	-0.42981706	0.31262594	-1.375
## address_22	0.00805815	0.25450330	0.032
## address_24	-0.11488722	0.25929307	-0.443
## address_13	-0.18287390	0.23661088	-0.773
## address_11	-0.00851662	0.23406302	-0.036
## address_1	-0.08382493	0.17514142	-0.479
## address_23	-0.06951789	0.25419416	-0.273
## address_26	0.12203288	0.27172620	0.449
## address_39	-0.41895961	0.31825961	-1.316
## address_42	0.34579034	0.38807231	0.891
## address_17	-0.00903240	0.24400929	-0.037
## address_34	0.03681511	0.30505709	0.121
## address_18	-0.03020161	0.24268533	-0.124
## address_28	0.04003076	0.26504997	0.151
## address_40	-0.36953494	0.33217137	-1.112
## address_45	-0.35331731	0.39269128	-0.900
## address_15	-0.10664044	0.23782480	-0.448
## address_46	-0.43767120	0.45348584	-0.965
## address_50	0.79501763	0.91317294	0.871
## address_33	-0.35059583	0.29636300	-1.183
## address_37	-0.45253587	0.32541230	-1.391
## address_7	-0.27515982	0.22255630	-1.236
## address_43	0.01450470	0.38374119	0.038
## address_41	-0.05757248	0.34204777	-0.168
## address_44	-0.39233230	0.37629755	-1.043
## address_47	0.09336105	0.42687314	0.219
## address_51	0.44166962	0.62417786	0.708
## address_49	0.45763670	0.59995320	0.763
## address_55	0.44387576	0.69368452	0.640
## address_48	-0.05259738	0.39598119	-0.133
## address_52	-1.10564463	0.76616394	-1.443
## address_53	0.58210288	0.76559199	0.760
## address_54	-0.07285986	1.28192304	-0.057
## carown_Lease	-0.07298849	0.06474099	-1.127
## `carown_N/A`	-0.75590974	0.22731822	-3.325
## cartype_Import	0.02069739	0.04462388	0.464
## `cartype_N/A`	NA	NA	NA
## commutebike_Yes	0.09442859	0.06459386	1.462
## reason_Convenience	0.22115889	0.08461657	2.614
## reason_Prices	-0.18314144	0.07469532	-2.452
## reason_Service	0.18941597	0.20182169	0.939
## reason_Other	-0.20651114	0.14882712	-1.388
## polview_Moderate	-0.06134514	0.06516523	-0.941
## `polview_Slightly conservative`	-0.04271156	0.07328199	-0.583

## `polview_Slightly liberal`	-0.11497170	0.07929323	-1.450
## polview_Liberal	-0.01679273	0.08002080	-0.210
## `polview_Extremely liberal`	-0.10684640	0.13100881	-0.816
## `polview_Extremely conservative`	-0.54539936	0.17409627	-3.133
## polcontrib_Yes	0.00490912	0.05153765	0.095
## vote_No	0.02312499	0.04401293	0.525
## card_Visa	0.04281189	0.06673973	0.641
## card_Discover	-0.02120147	0.06688167	-0.317
## card_Other	0.03232410	0.11108033	0.291
## `card_American Express`	0.61018542	0.07343112	8.310
## cardtype_Other	0.14258207	0.05994568	2.379
## cardtype_Gold	0.09949933	0.05975772	1.665
## cardtype_Platinum	0.03601710	0.05940127	0.606
## cardbenefit_Other	0.08819895	0.05991422	1.472
## `cardbenefit_Cash back`	0.06935353	0.06027168	1.151
## `cardbenefit_Airline miles`	0.05666919	0.05920487	0.957
## cardfee_Yes	-0.02844970	0.05399748	-0.527
## card2_Discover	-0.11174355	0.09464254	-1.181
## card2_Mastercard	-0.19365728	0.09284366	-2.086
## `card2_American Express`	0.40454440	0.10079660	4.013
## card2_Visa	-0.13583978	0.09396779	-1.446
## card2type_None	0.08767290	0.06034070	1.453
## card2type_Gold	-0.00814959	0.05948013	-0.137
## card2type_Other	0.02368243	0.05864442	0.404
## `card2benefit_Airline miles`	-0.05450746	0.05981524	-0.911
## card2benefit_Other	0.03465276	0.05954244	0.582
## `card2benefit_Cash back`	0.02241328	0.06004380	0.373
## card2fee_Yes	0.10532395	0.05403990	1.949
## active_Yes	-0.02244068	0.04487629	-0.500
## `bfast_Energy bar`	0.00546388	0.05294530	0.103
## bfast_Oatmeal	-0.06069318	0.05975190	-1.016
## churn_No	-0.08509279	0.05643230	-1.508
## tollfree_No	0.06783040	0.07622704	0.890
## equip_No	0.06246459	0.06397208	0.976
## callcard_No	-0.09853112	0.06021930	-1.636
## wireless_Yes	0.12479668	0.09056195	1.378
## multline_No	0.00403647	0.05392225	0.075
## voice_No	-0.07948692	0.06819764	-1.166
## pager_No	0.12125585	0.07255543	1.671
## internet_Other	0.06784565	0.10028063	0.677
## internet_DSL	-0.06830071	0.09266118	-0.737
## `internet_Cable modem`	-0.06493017	0.09257026	-0.701
## `internet_Dia-up`	0.00064387	0.08209999	0.008
## callid_Yes	0.03385622	0.06279174	0.539
## callwait_No	0.09715885	0.06275970	1.548
## forward_No	0.04596418	0.06231682	0.738
## confer_No	-0.04351673	0.06432521	-0.677
## ebill_Yes	0.02141591	0.06051085	0.354
## owntv_No	0.29579768	0.19697955	1.502
## ownvcr_No	0.07223014	0.09586350	0.753
## owndvd_No	0.01647664	0.09470029	0.174
## ownacd_Yes	0.12216660	0.10475481	1.166
## ownpda_Yes	-0.10468998	0.06848494	-1.529
## ownpc_Yes	-0.03496883	0.07034934	-0.497

## ownipod_No	0.00363586	0.05120243	0.071
## owngame_No	-0.05761714	0.05188234	-1.111
## ownfax_Yes	0.03154471	0.07252440	0.435
## news_Yes	-0.03418979	0.05204889	-0.657
## response_03_Yes	0.13358594	0.06920118	1.930
## edcat.L	-0.16044235	0.22662837	-0.708
## edcat.Q	0.06369961	0.06120442	1.041
## edcat.C	-0.01599009	0.04854237	-0.329
## edcat^4	0.04055652	0.04574734	0.887
## inccat.L	-0.61319701	0.21453182	-2.858
## inccat.Q	-0.36598625	0.07391583	-4.951
## inccat.C	-0.05329064	0.05647462	-0.944
## inccat^4	-0.02243750	0.05406938	-0.415
## jobsat.L	0.04922568	0.05909628	0.833
## jobsat.Q	-0.04252528	0.04981372	-0.854
## jobsat.C	0.08091540	0.04807390	1.683
## jobsat^4	0.03884907	0.04605652	0.844
## addresscat.L	NA	NA	NA
## addresscat.Q	NA	NA	NA
## addresscat.C	NA	NA	NA
## addresscat^4	NA	NA	NA
## carcatvalue.L	-0.53712998	0.17149614	-3.132
## carcatvalue.Q	0.31565525	0.13349389	2.365
## carcatvalue.C	NA	NA	NA
## cardtenure.L	-0.88437681	0.57045824	-1.550
## cardtenure.Q	0.51049755	0.39203359	1.302
## cardtenure.C	-0.49459117	0.33412208	-1.480
## cardtenure^4	0.07501509	0.30740360	0.244
## cardtenure^5	-0.26215427	0.28410180	-0.923
## cardtenure^6	0.06944549	0.26173225	0.265
## cardtenure^7	0.04181811	0.23974281	0.174
## cardtenure^8	-0.14618627	0.21798456	-0.671
## cardtenure^9	-0.36476140	0.19849890	-1.838
## cardtenure^10	-0.12300332	0.18330987	-0.671
## cardtenure^11	-0.27249801	0.16800766	-1.622
## cardtenure^12	-0.17606061	0.15752215	-1.118
## cardtenure^13	0.00043397	0.15083370	0.003
## cardtenure^14	-0.09196210	0.14712750	-0.625
## cardtenure^15	-0.02678449	0.14490211	-0.185
## cardtenure^16	0.10540772	0.14657754	0.719
## cardtenure^17	0.13447534	0.14343997	0.938
## cardtenure^18	0.10143946	0.14243716	0.712
## cardtenure^19	-0.12386763	0.14500349	-0.854
## cardtenure^20	0.19364633	0.14551932	1.331
## cardtenure^21	0.05750672	0.14579059	0.394
## cardtenure^22	-0.25131236	0.14775027	-1.701
## cardtenure^23	0.06041752	0.14892165	0.406
## cardtenure^24	0.07105478	0.14700246	0.483
## cardtenure^25	0.37338447	0.14539277	2.568
## cardtenure^26	0.01194626	0.14595676	0.082
## cardtenure^27	0.16246080	0.14713587	1.104
## cardtenure^28	0.10821231	0.14733221	0.734
## cardtenure^29	0.01158058	0.14724177	0.079
## cardtenure^30	0.05039167	0.14827082	0.340

## cardtenure^31	-0.26281379	0.15177497	-1.732
## cardtenure^32	-0.06373685	0.15250729	-0.418
## cardtenure^33	0.01491576	0.15079061	0.099
## cardtenure^34	0.05087551	0.13688226	0.372
## cardtenure^35	0.28035264	0.13525980	2.073
## cardtenure^36	0.11916023	0.15344377	0.777
## cardtenure^37	0.14300040	0.13737893	1.041
## cardtenure^38	0.01905715	0.14064833	0.135
## cardtenure^39	-0.01258357	0.14297808	-0.088
## cardtenure^40	0.09044948	0.15244941	0.593
## card2tenure.L	0.36313777	0.49197915	0.738
## card2tenure.Q	-0.35786356	0.36283555	-0.986
## card2tenure.C	0.44137303	0.32405987	1.362
## card2tenure^4	-0.17082085	0.29882640	-0.572
## card2tenure^5	-0.05631070	0.27373097	-0.206
## card2tenure^6	-0.08388046	0.24346458	-0.345
## card2tenure^7	-0.11409103	0.21409588	-0.533
## card2tenure^8	0.11351180	0.18819630	0.603
## card2tenure^9	0.22964563	0.16528114	1.389
## card2tenure^10	0.17975280	0.14863535	1.209
## card2tenure^11	-0.18414073	0.13597557	-1.354
## card2tenure^12	0.11560752	0.12921691	0.895
## card2tenure^13	0.08981021	0.12492896	0.719
## card2tenure^14	0.03103545	0.12415835	0.250
## card2tenure^15	0.02689017	0.12493885	0.215
## card2tenure^16	0.00003673	0.12429860	0.000
## card2tenure^17	-0.17692937	0.12443987	-1.422
## card2tenure^18	-0.08281831	0.12493006	-0.663
## card2tenure^19	0.11048333	0.12560228	0.880
## card2tenure^20	0.14959990	0.12383303	1.208
## card2tenure^21	0.17452196	0.12705007	1.374
## card2tenure^22	-0.01824734	0.12455091	-0.147
## card2tenure^23	0.02123354	0.12550792	0.169
## card2tenure^24	0.10521503	0.12528129	0.840
## card2tenure^25	0.21502681	0.12636988	1.702
## card2tenure^26	0.19010850	0.12399104	1.533
## card2tenure^27	0.13128064	0.12393168	1.059
## card2tenure^28	-0.07475545	0.12745550	-0.587
## card2tenure^29	0.06541995	0.13200516	0.496
## card2tenure^30	-0.13986422	0.12494525	-1.119
##	Pr(> t)		
## (Intercept)	< 0.0000000000000002 ***		
## ed	0.959230		
## lninc	0.0000000777 ***		
## lncreddebt	0.350536		
## othdebt	0.552405		
## carditems	< 0.0000000000000002 ***		
## cardspent	< 0.0000000000000002 ***		
## card2spent	< 0.0000000000000002 ***		
## tollten	0.593396		
## wireten	0.339414		
## total_spent	NA		
## `region_zone 5`	0.858323		
## `region_zone 3`	0.376740		

## `region_zone 4`	0.644813
## `region_zone 2`	0.945312
## gender_Male	0.706260
## `agecat_>65`	0.095979 .
## `agecat_25-34`	0.934908
## `agecat_50-64`	0.238855
## `agecat_35-49`	0.161110
## employ_16	0.488364
## employ_1	0.493609
## employ_22	0.420860
## employ_10	0.129666
## employ_11	0.238104
## employ_15	0.391446
## employ_19	0.925259
## employ_8	0.037647 *
## employ_4	0.139971
## employ_12	0.534292
## employ_3	0.373608
## employ_27	0.743569
## employ_31	0.812877
## employ_24	0.135899
## employ_29	0.922655
## employ_2	0.124377
## employ_18	0.156681
## employ_5	0.025838 *
## employ_28	0.325908
## employ_26	0.263867
## employ_23	0.806139
## employ_13	0.629442
## employ_17	0.534748
## employ_30	0.352293
## employ_14	0.099149 .
## employ_6	0.498908
## employ_36	0.804348
## employ_7	0.857975
## employ_9	0.050405 .
## employ_21	0.638181
## employ_20	0.126958
## employ_34	0.546308
## employ_35	0.391455
## employ_33	0.455306
## employ_25	0.451386
## employ_39	0.768829
## employ_45	0.111763
## employ_32	0.771563
## employ_40	0.649968
## employ_37	0.500543
## employ_48	0.923344
## employ_38	0.789263
## employ_46	0.918683
## employ_43	0.877537
## employ_47	0.902760
## employ_41	0.108084
## employ_42	0.316469

## employ_49	0.973125
## employ_44	0.277472
## employ_52	0.558424
## employ_51	0.375629
## `empcat_More than 15`	NA
## `empcat_6 to 10`	NA
## `empcat_11 to 15`	NA
## `empcat_2 to 5`	NA
## retire_Yes	0.241337
## `spousedcat_High school degree`	0.807101
## `spousedcat_College degree`	0.300320
## `spousedcat_Some college`	0.311796
## `spousedcat_Did not complete high school`	0.413384
## `spousedcat_Post-undergraduate degree`	0.674012
## homeown_Own	0.211320
## `hometype_Condominium/Townhouse`	0.612910
## `hometype_Single-family`	0.230218
## `hometype_Mobile Home`	0.464948
## address_2	0.569615
## address_30	0.527806
## address_3	0.470638
## address_31	0.351382
## address_21	0.149057
## address_20	0.086779
## address_19	0.440729
## address_14	0.693287
## address_5	0.279872
## address_9	0.768412
## address_32	0.601685
## address_29	0.208034
## address_8	0.397744
## address_12	0.250764
## address_10	0.489794
## address_38	0.638294
## address_4	0.841342
## address_57	0.587929
## address_16	0.876471
## address_27	0.240186
## address_6	0.578214
## address_35	0.834428
## address_25	0.304840
## address_36	0.169271
## address_22	0.974743
## address_24	0.657739
## address_13	0.439645
## address_11	0.970977
## address_1	0.632247
## address_23	0.784499
## address_26	0.653388
## address_39	0.188131
## address_42	0.372971
## address_17	0.970474
## address_34	0.903950
## address_18	0.900969

## address_28	0.879961	
## address_40	0.266014	
## address_45	0.368330	
## address_15	0.653895	
## address_46	0.334554	
## address_50	0.384032	
## address_33	0.236899	
## address_37	0.164427	
## address_7	0.216415	
## address_43	0.969851	
## address_41	0.866344	
## address_44	0.297207	
## address_47	0.826891	
## address_51	0.479244	
## address_49	0.445646	
## address_55	0.522295	
## address_48	0.894338	
## address_52	0.149092	
## address_53	0.447113	
## address_54	0.954679	
## carown_Lease	0.259661	
## `carown_N/A`	0.000893	***
## cartype_Import	0.642809	
## `cartype_N/A`	NA	
## commutebike_Yes	0.143871	
## reason_Convenience	0.009000	**
## reason_Prices	0.014265	*
## reason_Service	0.348042	
## reason_Other	0.165358	
## polview_Moderate	0.346582	
## `polview_Slightly conservative`	0.560043	
## `polview_Slightly liberal`	0.147168	
## polview_Liberal	0.833795	
## `polview_Extremely liberal`	0.414809	
## `polview_Extremely conservative`	0.001747	**
## polcontrib_Yes	0.924120	
## vote_No	0.599332	
## card_Visa	0.521260	
## card_Discover	0.751264	
## card_Other	0.771072	
## `card_American Express`	< 0.0000000000000002	***
## cardtype_Other	0.017440	*
## cardtype_Gold	0.096001	.
## cardtype_Platinum	0.544335	
## cardbenefit_Other	0.141095	
## `cardbenefit_Cash back`	0.249949	
## `cardbenefit_Airline miles`	0.338553	
## cardfee_Yes	0.598320	
## card2_Discover	0.237813	
## card2_Mastercard	0.037072	*
## `card2_American Express`	0.0000611986	***
## card2_Visa	0.148387	
## card2type_None	0.146331	
## card2type_Gold	0.891029	

## card2type_Other	0.686364
## `card2benefit_Airline miles`	0.362225
## card2benefit_Other	0.560618
## `card2benefit_Cash back`	0.708963
## card2fee_Yes	0.051382 .
## active_Yes	0.617070
## `bfast_Energy bar`	0.917812
## bfast_Oatmeal	0.309823
## churn_No	0.131685
## tollfree_No	0.373615
## equip_No	0.328922
## callcard_No	0.101895
## wireless_Yes	0.168291
## multline_No	0.940333
## voice_No	0.243888
## pager_No	0.094776 .
## internet_Other	0.498735
## internet_DSL	0.461114
## `internet_Cable modem`	0.483095
## `internet_Dia-up`	0.993743
## callid_Yes	0.589798
## callwait_No	0.121695
## forward_No	0.460818
## confer_No	0.498765
## ebill_Yes	0.723423
## owntv_No	0.133281
## ownvcr_No	0.451224
## owndvd_No	0.861886
## owncd_Yes	0.243614
## ownpda_Yes	0.126448
## ownpc_Yes	0.619171
## ownipod_No	0.943395
## owngame_No	0.266852
## ownfax_Yes	0.663626
## news_Yes	0.511306
## response_03_Yes	0.053645 .
## edcat.L	0.479026
## edcat.Q	0.298062
## edcat.C	0.741871
## edcat^4	0.375397
## inccat.L	0.004287 **
## inccat.Q	0.0000007749 ***
## inccat.C	0.345434
## inccat^4	0.678187
## jobsat.L	0.404921
## jobsat.Q	0.393343
## jobsat.C	0.092444 .
## jobsat^4	0.399007
## addresscat.L	NA
## addresscat.Q	NA
## addresscat.C	NA
## addresscat^4	NA
## carcatvalue.L	0.001752 **
## carcatvalue.Q	0.018110 *

## carcatvalue.C	NA
## cardtenure.L	0.121170
## cardtenure.Q	0.192949
## cardtenure.C	0.138899
## cardtenure^4	0.807225
## cardtenure^5	0.356208
## cardtenure^6	0.790772
## cardtenure^7	0.861539
## cardtenure^8	0.502507
## cardtenure^9	0.066214 .
## cardtenure^10	0.502260
## cardtenure^11	0.104915
## cardtenure^12	0.263784
## cardtenure^13	0.997705
## cardtenure^14	0.531982
## cardtenure^15	0.853362
## cardtenure^16	0.472116
## cardtenure^17	0.348571
## cardtenure^18	0.476411
## cardtenure^19	0.393036
## cardtenure^20	0.183374
## cardtenure^21	0.693277
## cardtenure^22	0.089054 .
## cardtenure^23	0.684990
## cardtenure^24	0.628875
## cardtenure^25	0.010270 *
## cardtenure^26	0.934773
## cardtenure^27	0.269609
## cardtenure^28	0.462711
## cardtenure^29	0.937316
## cardtenure^30	0.733982
## cardtenure^31	0.083441 .
## cardtenure^32	0.676029
## cardtenure^33	0.921210
## cardtenure^34	0.710160
## cardtenure^35	0.038280 *
## cardtenure^36	0.437468
## cardtenure^37	0.297991
## cardtenure^38	0.892229
## cardtenure^39	0.929874
## cardtenure^40	0.553017
## card2tenure.L	0.460498
## card2tenure.Q	0.324062
## card2tenure.C	0.173290
## card2tenure^4	0.567607
## card2tenure^5	0.837026
## card2tenure^6	0.730471
## card2tenure^7	0.594142
## card2tenure^8	0.546447
## card2tenure^9	0.164800
## card2tenure^10	0.226616
## card2tenure^11	0.175762
## card2tenure^12	0.371026
## card2tenure^13	0.472261

```
## card2tenure^14 0.802629
## card2tenure^15 0.829604
## card2tenure^16 0.999764
## card2tenure^17 0.155180
## card2tenure^18 0.507431
## card2tenure^19 0.379127
## card2tenure^20 0.227106
## card2tenure^21 0.169647
## card2tenure^22 0.883532
## card2tenure^23 0.865665
## card2tenure^24 0.401066
## card2tenure^25 0.088933
## card2tenure^26 0.125314
## card2tenure^27 0.289544
## card2tenure^28 0.557566
## card2tenure^29 0.620220
## card2tenure^30 0.263052
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.202 on 3211 degrees of freedom
## Multiple R-squared:  0.9703, Adjusted R-squared:  0.9677
## F-statistic: 364.8 on 288 and 3211 DF,  p-value: < 0.00000000000000022
```

This model still has variables that are not significant

```
fit2 <- lm(total_spent_sqrt~ed+lncreddebt+carditems+cardspent+card2spent+`agecat_>65`+`agecat_50-64`+
`agecat_35-49`+employ_1+employ_10+employ_11+employ_15+employ_8+employ_12+employ_27+
employ_2+employ_18+employ_15+employ_28+employ_26+employ_7+employ_9+employ_20+employ_34+emp
employ_38+`spousedcat_College degree`+`carown_N/A`+`card_American Express`+cardtype_Other+
cardtype_Platinum+card2_Discover+card2_Mastercard+`card2_American Express`+card2_Visa+
churn_No+voice_No+pager_No,data = Dev)
summary(fit2)
```

```
##
## Call:
## lm(formula = total_spent_sqrt ~ ed + lncreddebt + carditems +
##   cardspent + card2spent + `agecat_>65` + `agecat_50-64` +
##   `agecat_35-49` + employ_1 + employ_10 + employ_11 + employ_15 +
##   employ_8 + employ_12 + employ_27 + employ_2 + employ_18 +
##   employ_15 + employ_28 + employ_26 + employ_7 + employ_9 +
##   employ_20 + employ_34 + employ_35 + employ_38 + `spousedcat_College degree` +
##   `carown_N/A` + `card_American Express` + cardtype_Other +
##   cardtype_Platinum + card2_Discover + card2_Mastercard + `card2_American Express` +
##   card2_Visa + churn_No + voice_No + pager_No, data = Dev)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -7.1335 -0.5344  0.2814  0.8302  2.4875
##
## Coefficients:
##              Estimate Std. Error t value
## (Intercept)    9.8515618  0.1687412  58.383
## ed             -0.0104987  0.0074234  -1.414
## lncreddebt      0.1066813  0.0179933   5.929
```

## carditems	0.2097505	0.0079854	26.267
## cardspent	0.0176011	0.0001563	112.583
## card2spent	0.0218682	0.0002092	104.510
## `agecat_>65`	-0.0451464	0.0656936	-0.687
## `agecat_50-64`	0.1357498	0.0638009	2.128
## `agecat_35-49`	0.2074566	0.0601877	3.447
## employ_1	-0.0365809	0.0812227	-0.450
## employ_10	-0.1206429	0.1205264	-1.001
## employ_11	-0.1190177	0.1124955	-1.058
## employ_15	-0.0564655	0.1369030	-0.412
## employ_8	-0.1418240	0.1125437	-1.260
## employ_12	-0.0169334	0.1352393	-0.125
## employ_27	-0.1063087	0.2361558	-0.450
## employ_2	-0.1365370	0.0869772	-1.570
## employ_18	-0.2428051	0.1711075	-1.419
## employ_28	-0.3359295	0.2932945	-1.145
## employ_26	-0.2610638	0.2153703	-1.212
## employ_7	0.0830489	0.1097625	0.757
## employ_9	-0.1704133	0.1147773	-1.485
## employ_20	-0.2649660	0.1640813	-1.615
## employ_34	-0.1492537	0.2559158	-0.583
## employ_35	-0.2796039	0.3745426	-0.747
## employ_38	0.1238703	0.3330160	0.372
## `spousedcat_College degree`	0.0597293	0.0793961	0.752
## `carown_N/A`	-0.1350345	0.0700827	-1.927
## `card_American Express`	0.4898189	0.0620085	7.899
## cardtype_Other	0.0854191	0.0514157	1.661
## cardtype_Platinum	-0.0106240	0.0508898	-0.209
## card2_Discover	-0.0446165	0.0926348	-0.482
## card2_Mastercard	-0.1649586	0.0883788	-1.866
## `card2_American Express`	0.4229675	0.0966373	4.377
## card2_Visa	-0.1175534	0.0892676	-1.317
## churn_No	-0.0871622	0.0517297	-1.685
## voice_No	-0.1190916	0.0575243	-2.070
## pager_No	0.0370644	0.0615685	0.602
##	Pr(> t)		
## (Intercept)	< 0.0000000000000002 ***		
## ed	0.157372		
## lncreddebt	0.00000000334775247 ***		
## carditems	< 0.0000000000000002 ***		
## cardspent	< 0.0000000000000002 ***		
## card2spent	< 0.0000000000000002 ***		
## `agecat_>65`	0.491986		
## `agecat_50-64`	0.033432 *		
## `agecat_35-49`	0.000574 ***		
## employ_1	0.652466		
## employ_10	0.316913		
## employ_11	0.290139		
## employ_15	0.680036		
## employ_8	0.207694		
## employ_12	0.900364		
## employ_27	0.652621		
## employ_2	0.116553		
## employ_18	0.155983		

```

## employ_28                                0.252137
## employ_26                                0.225533
## employ_7                                  0.449327
## employ_9                                  0.137706
## employ_20                                0.106435
## employ_34                                0.559787
## employ_35                                0.455404
## employ_38                                0.709942
## `spousedcat_College degree`              0.451925
## `carown_N/A`                             0.054088 .
## `card_American Express`                  0.00000000000000374 ***
## cardtype_Other                           0.096735 .
## cardtype_Platinum                        0.834644
## card2_Discover                           0.630093
## card2_Mastercard                         0.062057 .
## `card2_American Express`                 0.00001239599924314 ***
## card2_Visa                               0.187971
## churn_No                                 0.092087 .
## voice_No                                 0.038500 *
## pager_No                                 0.547212
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.229 on 3462 degrees of freedom
## Multiple R-squared:  0.9666, Adjusted R-squared:  0.9662
## F-statistic: 2707 on 37 and 3462 DF, p-value: < 0.00000000000000022

```

To get the best model, a stepwise regression is done

Stepwise regression is used to get better valid predictors

```
step(fit2,direction = "both")
```

```

## Start: AIC=1480.2
## total_spent_sqrt ~ ed + lncrdebt + carditems + cardspent +
##   card2spent + `agecat_>65` + `agecat_50-64` + `agecat_35-49` +
##   employ_1 + employ_10 + employ_11 + employ_15 + employ_8 +
##   employ_12 + employ_27 + employ_2 + employ_18 + employ_15 +
##   employ_28 + employ_26 + employ_7 + employ_9 + employ_20 +
##   employ_34 + employ_35 + employ_38 + `spousedcat_College degree` +
##   `carown_N/A` + `card_American Express` + cardtype_Other +
##   cardtype_Platinum + card2_Discover + card2_Mastercard + `card2_American Express` +
##   card2_Visa + churn_No + voice_No + pager_No
##
##
##           Df Sum of Sq    RSS    AIC
## - employ_12      1      0.0  5227.7 1478.2
## - cardtype_Platinum 1      0.1  5227.7 1478.2
## - employ_38      1      0.2  5227.9 1478.3
## - employ_15      1      0.3  5227.9 1478.4
## - employ_27      1      0.3  5228.0 1478.4
## - employ_1       1      0.3  5228.0 1478.4
## - card2_Discover  1      0.4  5228.0 1478.4
## - employ_34      1      0.5  5228.2 1478.5
## - pager_No       1      0.5  5228.2 1478.6

```



```

## - `agecat_>65` 1 0.7 5228.4 1478.7
## - employ_35 1 0.8 5228.5 1478.8
## - `spousedcat_College degree` 1 0.9 5228.5 1478.8
## - employ_7 1 0.9 5228.5 1478.8
## - employ_10 1 1.5 5229.2 1479.2
## - employ_11 1 1.7 5229.3 1479.3
## - employ_28 1 2.0 5229.6 1479.5
## - employ_26 1 2.2 5229.9 1479.7
## - employ_8 1 2.4 5230.1 1479.8
## - card2_Visa 1 2.6 5230.3 1480.0
## <none> 5227.7 1480.2
## - ed 1 3.0 5230.7 1480.2
## - employ_18 1 3.0 5230.7 1480.2
## - employ_9 1 3.3 5231.0 1480.4
## - employ_2 1 3.7 5231.4 1480.7
## - employ_20 1 3.9 5231.6 1480.8
## - cardtype_Other 1 4.2 5231.8 1481.0
## - churn_No 1 4.3 5231.9 1481.1
## - card2_Mastercard 1 5.3 5232.9 1481.7
## - `carown_N/A` 1 5.6 5233.3 1482.0
## - voice_No 1 6.5 5234.1 1482.5
## - `agecat_50-64` 1 6.8 5234.5 1482.8
## - `agecat_35-49` 1 17.9 5245.6 1490.2
## - `card2_American Express` 1 28.9 5256.6 1497.5
## - lncreddebt 1 53.1 5280.7 1513.6
## - `card_American Express` 1 94.2 5321.9 1540.7
## - carditems 1 1041.8 6269.5 2114.3
## - card2spent 1 16492.7 21720.4 6463.2
## - cardspent 1 19139.3 24367.0 6865.6
##
## Step: AIC=1478.22
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
## card2spent + `agecat_>65` + `agecat_50-64` + `agecat_35-49` +
## employ_1 + employ_10 + employ_11 + employ_15 + employ_8 +
## employ_27 + employ_2 + employ_18 + employ_28 + employ_26 +
## employ_7 + employ_9 + employ_20 + employ_34 + employ_35 +
## employ_38 + `spousedcat_College degree` + `carown_N/A` +
## `card_American Express` + cardtype_Other + cardtype_Platinum +
## card2_Discover + card2_Mastercard + `card2_American Express` +
## card2_Visa + churn_No + voice_No + pager_No
##
## Df Sum of Sq RSS AIC
## - cardtype_Platinum 1 0.1 5227.7 1476.3
## - employ_38 1 0.2 5227.9 1476.4
## - employ_15 1 0.2 5227.9 1476.4
## - employ_1 1 0.3 5228.0 1476.4
## - employ_27 1 0.3 5228.0 1476.4
## - card2_Discover 1 0.4 5228.0 1476.5
## - employ_34 1 0.5 5228.2 1476.6
## - pager_No 1 0.5 5228.2 1476.6
## - `agecat_>65` 1 0.7 5228.4 1476.7
## - employ_35 1 0.8 5228.5 1476.8
## - `spousedcat_College degree` 1 0.8 5228.5 1476.8
## - employ_7 1 0.9 5228.6 1476.8

```

```

## - employ_10          1          1.5  5229.2 1477.2
## - employ_11          1          1.7  5229.4 1477.3
## - employ_28          1          2.0  5229.7 1477.5
## - employ_26          1          2.2  5229.9 1477.7
## - employ_8           1          2.4  5230.1 1477.8
## - card2_Visa         1          2.6  5230.3 1478.0
## <none>                5227.7 1478.2
## - ed                 1          3.0  5230.7 1478.2
## - employ_18          1          3.0  5230.7 1478.2
## - employ_9           1          3.3  5231.0 1478.4
## - employ_2           1          3.7  5231.4 1478.7
## - employ_20          1          3.9  5231.6 1478.8
## - cardtype_Other     1          4.2  5231.8 1479.0
## - churn_No           1          4.3  5232.0 1479.1
## - card2_Mastercard   1          5.3  5233.0 1479.7
## - `carown_N/A`       1          5.6  5233.3 1480.0
## + employ_12          1          0.0  5227.7 1480.2
## - voice_No           1          6.5  5234.1 1480.5
## - `agecat_50-64`     1          6.8  5234.5 1480.8
## - `agecat_35-49`     1         18.0  5245.7 1488.2
## - `card2_American Express` 1         28.9  5256.6 1495.5
## - lncreddebt         1         53.1  5280.7 1511.6
## - `card_American Express` 1         94.3  5322.0 1538.8
## - carditems          1        1042.2  6269.9 2112.5
## - card2spent         1       16496.6 21724.3 6461.8
## - cardspent          1       19140.5 24368.2 6863.8
##
## Step:  AIC=1476.26
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_>65` + `agecat_50-64` + `agecat_35-49` +
##   employ_1 + employ_10 + employ_11 + employ_15 + employ_8 +
##   employ_27 + employ_2 + employ_18 + employ_28 + employ_26 +
##   employ_7 + employ_9 + employ_20 + employ_34 + employ_35 +
##   employ_38 + `spousedcat_College degree` + `carown_N/A` +
##   `card_American Express` + cardtype_Other + card2_Discover +
##   card2_Mastercard + `card2_American Express` + card2_Visa +
##   churn_No + voice_No + pager_No
##
##              Df Sum of Sq      RSS      AIC
## - employ_38    1         0.2  5228.0 1474.4
## - employ_15    1         0.2  5228.0 1474.4
## - employ_27    1         0.3  5228.0 1474.5
## - employ_1     1         0.3  5228.1 1474.5
## - card2_Discover 1         0.4  5228.1 1474.5
## - employ_34    1         0.5  5228.3 1474.6
## - pager_No     1         0.5  5228.3 1474.6
## - `agecat_>65` 1         0.7  5228.5 1474.7
## - employ_35    1         0.8  5228.6 1474.8
## - `spousedcat_College degree` 1         0.8  5228.6 1474.8
## - employ_7     1         0.9  5228.6 1474.8
## - employ_10    1         1.5  5229.3 1475.3
## - employ_11    1         1.7  5229.4 1475.4
## - employ_28    1         2.0  5229.7 1475.6
## - employ_26    1         2.2  5230.0 1475.7

```

```

## - employ_8          1      2.4  5230.1 1475.8
## - card2_Visa        1      2.6  5230.4 1476.0
## <none>              5227.7 1476.3
## - employ_18        1      3.0  5230.8 1476.3
## - ed                1      3.0  5230.8 1476.3
## - employ_9         1      3.3  5231.1 1476.5
## - employ_2         1      3.7  5231.4 1476.7
## - employ_20        1      3.9  5231.7 1476.9
## - churn_No         1      4.3  5232.0 1477.1
## - cardtype_Other   1      5.1  5232.8 1477.6
## - card2_Mastercard  1      5.3  5233.0 1477.8
## - `carown_N/A`     1      5.6  5233.3 1478.0
## + cardtype_Platinum 1      0.1  5227.7 1478.2
## + employ_12        1      0.0  5227.7 1478.2
## - voice_No         1      6.5  5234.2 1478.6
## - `agecat_50-64`   1      6.8  5234.6 1478.8
## - `agecat_35-49`   1     18.0  5245.7 1486.3
## - `card2_American Express` 1    28.9  5256.6 1493.6
## - lncreddebt       1     53.0  5280.8 1509.6
## - `card_American Express` 1    94.3  5322.0 1536.8
## - carditems        1    1043.7  6271.4 2111.3
## - card2spent       1   16527.6 21755.3 6464.8
## - cardspent        1   19163.2 24391.0 6865.1
##
## Step: AIC=1474.4
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_>65` + `agecat_50-64` + `agecat_35-49` +
##   employ_1 + employ_10 + employ_11 + employ_15 + employ_8 +
##   employ_27 + employ_2 + employ_18 + employ_28 + employ_26 +
##   employ_7 + employ_9 + employ_20 + employ_34 + employ_35 +
##   `spousedcat_College degree` + `carown_N/A` + `card_American Express` +
##   cardtype_Other + card2_Discover + card2_Mastercard + `card2_American Express` +
##   card2_Visa + churn_No + voice_No + pager_No
##
##           Df Sum of Sq    RSS    AIC
## - employ_15      1      0.3  5228.2 1472.6
## - employ_27      1      0.3  5228.3 1472.6
## - employ_1       1      0.3  5228.3 1472.6
## - card2_Discover  1      0.3  5228.3 1472.6
## - employ_34      1      0.5  5228.5 1472.8
## - pager_No       1      0.6  5228.5 1472.8
## - `agecat_>65`   1      0.7  5228.6 1472.8
## - `spousedcat_College degree` 1      0.8  5228.8 1473.0
## - employ_35      1      0.9  5228.8 1473.0
## - employ_7       1      0.9  5228.8 1473.0
## - employ_10      1      1.5  5229.5 1473.4
## - employ_11      1      1.7  5229.7 1473.5
## - employ_28      1      2.0  5229.9 1473.7
## - employ_26      1      2.2  5230.2 1473.9
## - employ_8       1      2.4  5230.4 1474.0
## - card2_Visa     1      2.6  5230.6 1474.1
## <none>           5228.0 1474.4
## - ed            1      3.0  5231.0 1474.4
## - employ_18     1      3.1  5231.0 1474.4

```

```

## - employ_9          1      3.3  5231.3 1474.6
## - employ_2          1      3.7  5231.7 1474.9
## - employ_20         1      3.9  5231.9 1475.0
## - churn_No          1      4.3  5232.2 1475.3
## - cardtype_Other     1      5.1  5233.0 1475.8
## - card2_Mastercard   1      5.2  5233.2 1475.9
## - `carown_N/A`      1      5.6  5233.5 1476.1
## + employ_38          1      0.2  5227.7 1476.3
## + cardtype_Platinum  1      0.1  5227.9 1476.4
## + employ_12          1      0.0  5227.9 1476.4
## - voice_No          1      6.5  5234.5 1476.8
## - `agecat_50-64`    1      6.8  5234.8 1477.0
## - `agecat_35-49`    1     18.0  5246.0 1484.4
## - `card2_American Express` 1     29.0  5257.0 1491.8
## - lncreddebt        1     53.2  5281.1 1507.8
## - `card_American Express` 1     94.3  5322.3 1535.0
## - carditems         1    1043.5  6271.5 2109.4
## - card2spent        1   16527.4 21755.4 6462.8
## - cardspent         1   19167.8 24395.8 6863.8
##
## Step: AIC=1472.57
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_>65` + `agecat_50-64` + `agecat_35-49` +
##   employ_1 + employ_10 + employ_11 + employ_8 + employ_27 +
##   employ_2 + employ_18 + employ_28 + employ_26 + employ_7 +
##   employ_9 + employ_20 + employ_34 + employ_35 + `spousedcat_College degree` +
##   `carown_N/A` + `card_American Express` + cardtype_Other +
##   card2_Discover + card2_Mastercard + `card2_American Express` +
##   card2_Visa + churn_No + voice_No + pager_No
##
##              Df Sum of Sq      RSS      AIC
## - employ_1          1      0.3  5228.5 1470.8
## - employ_27         1      0.3  5228.5 1470.8
## - card2_Discover     1      0.4  5228.6 1470.8
## - employ_34          1      0.5  5228.7 1470.9
## - pager_No          1      0.6  5228.8 1470.9
## - `agecat_>65`      1      0.7  5228.9 1471.1
## - employ_35          1      0.8  5229.0 1471.1
## - `spousedcat_College degree` 1      0.9  5229.1 1471.1
## - employ_7          1      0.9  5229.1 1471.2
## - employ_10         1      1.5  5229.7 1471.6
## - employ_11         1      1.6  5229.8 1471.7
## - employ_28         1      2.0  5230.2 1471.9
## - employ_26         1      2.2  5230.4 1472.0
## - employ_8          1      2.3  5230.5 1472.1
## - card2_Visa        1      2.6  5230.8 1472.3
## - employ_18         1      3.0  5231.2 1472.6
## <none>              5228.2 1472.6
## - ed                1      3.0  5231.2 1472.6
## - employ_9          1      3.2  5231.4 1472.7
## - employ_2          1      3.6  5231.8 1473.0
## - employ_20         1      3.9  5232.1 1473.2
## - churn_No          1      4.3  5232.5 1473.4
## - cardtype_Other     1      5.1  5233.3 1474.0

```

```

## - card2_Mastercard          1      5.2  5233.5 1474.1
## - `carown_N/A`             1      5.6  5233.8 1474.3
## + employ_15                 1      0.3  5228.0 1474.4
## + employ_38                 1      0.2  5228.0 1474.4
## + cardtype_Platinum         1      0.1  5228.2 1474.5
## + employ_12                 1      0.0  5228.2 1474.6
## - voice_No                  1      6.6  5234.8 1475.0
## - `agecat_50-64`            1      6.6  5234.8 1475.0
## - `agecat_35-49`            1     17.8  5246.0 1482.4
## - `card2_American Express`  1     29.0  5257.2 1489.9
## - lncreddebt                1     53.0  5281.2 1505.9
## - `card_American Express`   1     94.6  5322.8 1533.3
## - carditems                 1    1044.9  6273.1 2108.3
## - card2spent                1   16536.7 21764.9 6462.4
## - cardspent                 1   19174.4 24402.6 6862.7
##
## Step:  AIC=1470.76
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_>65` + `agecat_50-64` + `agecat_35-49` +
##   employ_10 + employ_11 + employ_8 + employ_27 + employ_2 +
##   employ_18 + employ_28 + employ_26 + employ_7 + employ_9 +
##   employ_20 + employ_34 + employ_35 + `spousedcat_College degree` +
##   `carown_N/A` + `card_American Express` + cardtype_Other +
##   card2_Discover + card2_Mastercard + `card2_American Express` +
##   card2_Visa + churn_No + voice_No + pager_No
##
##
##           Df Sum of Sq      RSS      AIC
## - employ_27          1      0.3  5228.8 1469.0
## - card2_Discover      1      0.4  5228.9 1469.0
## - employ_34           1      0.5  5229.0 1469.1
## - pager_No           1      0.6  5229.1 1469.1
## - `agecat_>65`        1      0.6  5229.1 1469.1
## - employ_35           1      0.8  5229.3 1469.3
## - `spousedcat_College degree` 1      0.9  5229.3 1469.3
## - employ_7            1      1.0  5229.5 1469.4
## - employ_10           1      1.4  5229.9 1469.7
## - employ_11           1      1.6  5230.1 1469.8
## - employ_28           1      1.9  5230.4 1470.1
## - employ_26           1      2.2  5230.7 1470.2
## - employ_8            1      2.2  5230.7 1470.2
## - card2_Visa          1      2.6  5231.1 1470.5
## - employ_18           1      2.9  5231.4 1470.7
## <none>                5228.5 1470.8
## - ed                  1      3.0  5231.5 1470.8
## - employ_9            1      3.1  5231.6 1470.9
## - employ_2            1      3.4  5231.9 1471.0
## - employ_20           1      3.8  5232.3 1471.3
## - churn_No            1      4.2  5232.7 1471.6
## - cardtype_Other      1      5.1  5233.6 1472.2
## - card2_Mastercard    1      5.2  5233.7 1472.2
## - `carown_N/A`        1      5.6  5234.1 1472.5
## + employ_1            1      0.3  5228.2 1472.6
## + employ_15            1      0.2  5228.3 1472.6
## + employ_38            1      0.2  5228.3 1472.6

```

```

## + cardtype_Platinum          1      0.1  5228.4 1472.7
## + employ_12                  1      0.0  5228.5 1472.8
## - voice_No                   1      6.6  5235.1 1473.2
## - `agecat_50-64`             1      7.5  5236.0 1473.8
## - `agecat_35-49`             1     18.6  5247.1 1481.2
## - `card2_American Express`   1     29.1  5257.6 1488.2
## - lncreddebt                 1     53.2  5281.7 1504.2
## - `card_American Express`    1     94.6  5323.1 1531.5
## - carditems                  1    1045.2  6273.7 2106.6
## - card2spent                 1   16545.7 21774.2 6461.9
## - cardspent                  1   19177.0 24405.5 6861.2
##
## Step:  AIC=1468.96
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_>65` + `agecat_50-64` + `agecat_35-49` +
##   employ_10 + employ_11 + employ_8 + employ_2 + employ_18 +
##   employ_28 + employ_26 + employ_7 + employ_9 + employ_20 +
##   employ_34 + employ_35 + `spousedcat_College degree` + `carown_N/A` +
##   `card_American Express` + cardtype_Other + card2_Discover +
##   card2_Mastercard + `card2_American Express` + card2_Visa +
##   churn_No + voice_No + pager_No
##
##              Df Sum of Sq      RSS      AIC
## - card2_Discover      1      0.4  5229.1 1467.2
## - employ_34           1      0.5  5229.3 1467.3
## - pager_No            1      0.6  5229.3 1467.3
## - `agecat_>65`        1      0.7  5229.4 1467.4
## - employ_35           1      0.8  5229.6 1467.5
## - `spousedcat_College degree` 1      0.8  5229.6 1467.5
## - employ_7            1      1.0  5229.8 1467.6
## - employ_10           1      1.4  5230.2 1467.9
## - employ_11           1      1.5  5230.3 1468.0
## - employ_28           1      1.9  5230.7 1468.2
## - employ_26           1      2.1  5230.9 1468.4
## - employ_8            1      2.2  5231.0 1468.4
## - card2_Visa          1      2.5  5231.3 1468.7
## - employ_18           1      2.9  5231.7 1468.9
## <none>                5228.8 1469.0
## - ed                  1      3.0  5231.8 1469.0
## - employ_9            1      3.1  5231.9 1469.0
## - employ_2            1      3.4  5232.2 1469.2
## - employ_20           1      3.8  5232.5 1469.5
## - churn_No           1      4.2  5233.0 1469.8
## - cardtype_Other      1      5.1  5233.9 1470.4
## - card2_Mastercard    1      5.2  5234.0 1470.4
## - `carown_N/A`       1      5.6  5234.3 1470.7
## + employ_27           1      0.3  5228.5 1470.8
## + employ_1            1      0.3  5228.5 1470.8
## + employ_38           1      0.2  5228.6 1470.8
## + employ_15           1      0.2  5228.6 1470.8
## + cardtype_Platinum   1      0.1  5228.7 1470.9
## + employ_12           1      0.0  5228.8 1471.0
## - voice_No           1      6.7  5235.4 1471.4
## - `agecat_50-64`     1      7.4  5236.1 1471.9

```

```

## - `agecat_35-49`      1      18.6  5247.3 1479.4
## - `card2_American Express` 1      29.1  5257.9 1486.4
## - lncreddebt          1      53.1  5281.9 1502.3
## - `card_American Express` 1      94.3  5323.1 1529.5
## - carditems           1    1045.2  6274.0 2104.8
## - card2spent          1   16545.6 21774.4 6459.9
## - cardspent           1   19178.8 24407.6 6859.5
##
## Step: AIC=1467.19
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_>65` + `agecat_50-64` + `agecat_35-49` +
##   employ_10 + employ_11 + employ_8 + employ_2 + employ_18 +
##   employ_28 + employ_26 + employ_7 + employ_9 + employ_20 +
##   employ_34 + employ_35 + `spousedcat_College degree` + `carown_N/A` +
##   `card_American Express` + cardtype_Other + card2_Mastercard +
##   `card2_American Express` + card2_Visa + churn_No + voice_No +
##   pager_No
##
##              Df Sum of Sq      RSS      AIC
## - employ_34      1         0.5  5229.6 1465.5
## - pager_No       1         0.6  5229.7 1465.6
## - `agecat_>65`   1         0.7  5229.8 1465.6
## - employ_35      1         0.8  5229.9 1465.7
## - `spousedcat_College degree` 1         0.8  5230.0 1465.8
## - employ_7       1         1.0  5230.1 1465.9
## - employ_10      1         1.4  5230.5 1466.1
## - employ_11      1         1.5  5230.6 1466.2
## - employ_28      1         1.9  5231.1 1466.5
## - employ_8       1         2.2  5231.3 1466.6
## - employ_26      1         2.2  5231.3 1466.7
## - employ_18      1         2.9  5232.1 1467.2
## <none>                                5229.1 1467.2
## - employ_9       1         3.2  5232.3 1467.3
## - card2_Visa     1         3.3  5232.4 1467.4
## - employ_2       1         3.3  5232.5 1467.4
## - ed             1         3.3  5232.5 1467.4
## - employ_20      1         3.7  5232.9 1467.7
## - churn_No       1         4.3  5233.4 1468.1
## - cardtype_Other 1         5.0  5234.2 1468.6
## - `carown_N/A`   1         5.6  5234.7 1468.9
## + card2_Discover 1         0.4  5228.8 1469.0
## + employ_1       1         0.3  5228.9 1469.0
## + employ_27      1         0.3  5228.9 1469.0
## + employ_15      1         0.2  5228.9 1469.0
## + employ_38      1         0.2  5228.9 1469.0
## + cardtype_Platinum 1         0.1  5229.1 1469.2
## + employ_12      1         0.0  5229.1 1469.2
## - voice_No       1         6.6  5235.8 1469.6
## - `agecat_50-64` 1         7.3  5236.4 1470.1
## - card2_Mastercard 1         8.4  5237.6 1470.8
## - `agecat_35-49` 1        18.5  5247.6 1477.5
## - lncreddebt     1        52.9  5282.0 1500.4
## - `card2_American Express` 1        66.5  5295.6 1509.4
## - `card_American Express` 1        95.5  5324.7 1528.5

```

```

## - carditems          1    1045.1  6274.3 2102.9
## - card2spent         1   16559.1 21788.3 6460.1
## - cardspent          1   19179.0 24408.1 6857.5
##
## Step: AIC=1465.52
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_>65` + `agecat_50-64` + `agecat_35-49` +
##   employ_10 + employ_11 + employ_8 + employ_2 + employ_18 +
##   employ_28 + employ_26 + employ_7 + employ_9 + employ_20 +
##   employ_35 + `spousedcat_College degree` + `carown_N/A` +
##   `card_American Express` + cardtype_Other + card2_Mastercard +
##   `card2_American Express` + card2_Visa + churn_No + voice_No +
##   pager_No
##
##              Df Sum of Sq    RSS    AIC
## - pager_No      1      0.6  5230.2 1463.9
## - employ_35      1      0.8  5230.4 1464.0
## - `agecat_>65`    1      0.8  5230.4 1464.1
## - `spousedcat_College degree` 1      0.9  5230.5 1464.1
## - employ_7       1      1.0  5230.7 1464.2
## - employ_10      1      1.4  5231.0 1464.4
## - employ_11      1      1.5  5231.1 1464.5
## - employ_28      1      1.9  5231.5 1464.8
## - employ_26      1      2.1  5231.8 1464.9
## - employ_8       1      2.1  5231.8 1464.9
## - employ_18      1      2.9  5232.5 1465.4
## <none>                                5229.6 1465.5
## - employ_9       1      3.1  5232.7 1465.6
## - ed             1      3.2  5232.9 1465.7
## - card2_Visa     1      3.2  5232.9 1465.7
## - employ_2       1      3.3  5232.9 1465.7
## - employ_20      1      3.7  5233.3 1466.0
## - churn_No       1      4.3  5234.0 1466.4
## - cardtype_Other 1      5.1  5234.7 1466.9
## + employ_34      1      0.5  5229.1 1467.2
## + card2_Discover 1      0.4  5229.3 1467.3
## - `carown_N/A`    1      5.7  5235.3 1467.3
## + employ_1       1      0.3  5229.4 1467.3
## + employ_27      1      0.3  5229.4 1467.4
## + employ_38      1      0.2  5229.4 1467.4
## + employ_15      1      0.2  5229.4 1467.4
## + cardtype_Platinum 1      0.1  5229.6 1467.5
## + employ_12      1      0.0  5229.6 1467.5
## - voice_No       1      6.6  5236.2 1467.9
## - `agecat_50-64` 1      7.3  5236.9 1468.4
## - card2_Mastercard 1      8.4  5238.0 1469.1
## - `agecat_35-49` 1     18.5  5248.1 1475.9
## - lncreddebt     1     52.5  5282.2 1498.5
## - `card2_American Express` 1     66.6  5296.2 1507.8
## - `card_American Express` 1     95.4  5325.1 1526.8
## - carditems      1    1045.4  6275.0 2101.3
## - card2spent     1   16573.2 21802.8 6460.5
## - cardspent      1   19179.0 24408.7 6855.6
##

```



```

## Step: AIC=1463.9
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_>65` + `agecat_50-64` + `agecat_35-49` +
##   employ_10 + employ_11 + employ_8 + employ_2 + employ_18 +
##   employ_28 + employ_26 + employ_7 + employ_9 + employ_20 +
##   employ_35 + `spousedcat_College degree` + `carown_N/A` +
##   `card_American Express` + cardtype_Other + card2_Mastercard +
##   `card2_American Express` + card2_Visa + churn_No + voice_No
##
##           Df Sum of Sq    RSS    AIC
## - `agecat_>65`           1      0.8 5231.0 1462.4
## - employ_35              1      0.8 5231.0 1462.4
## - `spousedcat_College degree` 1      0.9 5231.1 1462.5
## - employ_7              1      1.1 5231.3 1462.6
## - employ_10             1      1.4 5231.6 1462.8
## - employ_11             1      1.4 5231.6 1462.9
## - employ_28             1      1.9 5232.1 1463.2
## - employ_8              1      2.1 5232.3 1463.3
## - employ_26             1      2.1 5232.3 1463.3
## - employ_18             1      2.9 5233.1 1463.8
## <none>                   5230.2 1463.9
## - employ_9              1      3.1 5233.3 1464.0
## - card2_Visa            1      3.2 5233.4 1464.0
## - employ_2              1      3.3 5233.5 1464.1
## - employ_20             1      3.7 5233.9 1464.4
## - ed                   1      3.7 5233.9 1464.4
## - churn_No              1      4.1 5234.3 1464.6
## - cardtype_Other        1      5.1 5235.3 1465.3
## + pager_No              1      0.6 5229.6 1465.5
## + employ_34             1      0.5 5229.7 1465.6
## - `carown_N/A`          1      5.6 5235.8 1465.6
## + card2_Discover        1      0.4 5229.8 1465.7
## + employ_1              1      0.3 5229.9 1465.7
## + employ_38             1      0.3 5229.9 1465.7
## + employ_27             1      0.3 5229.9 1465.7
## + employ_15             1      0.2 5230.0 1465.8
## + cardtype_Platinum     1      0.1 5230.1 1465.9
## + employ_12             1      0.0 5230.2 1465.9
## - voice_No              1      6.5 5236.7 1466.3
## - `agecat_50-64`        1      7.1 5237.3 1466.7
## - card2_Mastercard      1      8.3 5238.5 1467.5
## - `agecat_35-49`        1     18.2 5248.4 1474.1
## - lncreddebt            1     52.5 5282.7 1496.9
## - `card2_American Express` 1     66.6 5296.8 1506.2
## - `card_American Express` 1     95.5 5325.7 1525.2
## - carditems             1    1047.2 6277.4 2100.7
## - card2spent            1   16591.2 21821.4 6461.5
## - cardspent             1   19202.4 24432.6 6857.0
##
## Step: AIC=1462.43
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_50-64` + `agecat_35-49` + employ_10 +
##   employ_11 + employ_8 + employ_2 + employ_18 + employ_28 +
##   employ_26 + employ_7 + employ_9 + employ_20 + employ_35 +

```

```
## `spousedcat_College degree` + `carown_N/A` + `card_American Express` +
## cardtype_Other + card2_Mastercard + `card2_American Express` +
## card2_Visa + churn_No + voice_No
```

	Df	Sum of Sq	RSS	AIC
## - `spousedcat_College degree`	1	0.9	5231.8	1461.0
## - employ_35	1	1.0	5231.9	1461.1
## - employ_7	1	1.0	5232.0	1461.1
## - employ_10	1	1.5	5232.5	1461.4
## - employ_11	1	1.7	5232.7	1461.5
## - employ_28	1	2.2	5233.1	1461.9
## - employ_8	1	2.2	5233.1	1461.9
## - employ_26	1	2.5	5233.4	1462.1
## <none>			5231.0	1462.4
## - employ_2	1	3.0	5234.0	1462.5
## - card2_Visa	1	3.2	5234.2	1462.6
## - employ_18	1	3.2	5234.2	1462.6
## - employ_9	1	3.3	5234.3	1462.6
## - ed	1	3.5	5234.5	1462.8
## - employ_20	1	4.0	5235.0	1463.1
## - churn_No	1	5.1	5236.0	1463.8
## - cardtype_Other	1	5.1	5236.1	1463.8
## + `agecat_>65`	1	0.8	5230.2	1463.9
## + employ_34	1	0.6	5230.3	1464.0
## + pager_No	1	0.5	5230.4	1464.1
## - `carown_N/A`	1	5.6	5236.6	1464.2
## + card2_Discover	1	0.4	5230.6	1464.2
## + employ_27	1	0.4	5230.6	1464.2
## + employ_15	1	0.3	5230.7	1464.2
## + employ_38	1	0.2	5230.8	1464.3
## + employ_1	1	0.1	5230.9	1464.4
## + cardtype_Platinum	1	0.1	5230.9	1464.4
## + employ_12	1	0.0	5231.0	1464.4
## - voice_No	1	6.7	5237.7	1464.9
## - card2_Mastercard	1	8.3	5239.3	1466.0
## - `agecat_50-64`	1	12.3	5243.3	1468.7
## - `agecat_35-49`	1	27.0	5257.9	1478.4
## - lncreddebt	1	52.0	5282.9	1495.0
## - `card2_American Express`	1	66.6	5297.6	1504.7
## - `card_American Express`	1	95.6	5326.6	1523.8
## - carditems	1	1050.9	6281.9	2101.2
## - card2spent	1	16610.5	21841.5	6462.7
## - cardspent	1	19209.1	24440.1	6856.1

```
##
## Step: AIC=1461.01
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
## card2spent + `agecat_50-64` + `agecat_35-49` + employ_10 +
## employ_11 + employ_8 + employ_2 + employ_18 + employ_28 +
## employ_26 + employ_7 + employ_9 + employ_20 + employ_35 +
## `carown_N/A` + `card_American Express` + cardtype_Other +
## card2_Mastercard + `card2_American Express` + card2_Visa +
## churn_No + voice_No
```

	Df	Sum of Sq	RSS	AIC
--	----	-----------	-----	-----

```

## - employ_35          1      0.9 5232.8 1459.6
## - employ_7           1      1.0 5232.9 1459.7
## - employ_10          1      1.4 5233.2 1459.9
## - employ_11          1      1.6 5233.5 1460.1
## - employ_28          1      2.1 5234.0 1460.4
## - employ_8           1      2.2 5234.1 1460.5
## - employ_26          1      2.5 5234.3 1460.6
## - ed                 1      3.0 5234.8 1461.0
## <none>               5231.8 1461.0
## - employ_2           1      3.0 5234.9 1461.0
## - employ_18          1      3.2 5235.0 1461.1
## - card2_Visa         1      3.2 5235.1 1461.2
## - employ_9           1      3.3 5235.1 1461.2
## - employ_20          1      4.1 5235.9 1461.7
## - churn_No           1      5.0 5236.9 1462.4
## + `spousedcat_College degree` 1      0.9 5231.0 1462.4
## - cardtype_Other     1      5.1 5237.0 1462.4
## + `agecat_>65`       1      0.8 5231.1 1462.5
## + employ_34          1      0.7 5231.2 1462.6
## + pager_No           1      0.6 5231.3 1462.6
## - `carown_N/A`       1      5.6 5237.4 1462.7
## + card2_Discover     1      0.4 5231.5 1462.8
## + employ_27          1      0.3 5231.5 1462.8
## + employ_15          1      0.3 5231.5 1462.8
## + employ_38          1      0.2 5231.7 1462.9
## + employ_1           1      0.1 5231.7 1462.9
## + cardtype_Platinum  1      0.0 5231.8 1463.0
## + employ_12          1      0.0 5231.8 1463.0
## - voice_No           1      6.8 5238.7 1463.6
## - card2_Mastercard   1      8.3 5240.2 1464.6
## - `agecat_50-64`     1     12.5 5244.3 1467.3
## - `agecat_35-49`     1     27.0 5258.9 1477.0
## - lncreddebt         1     51.5 5283.4 1493.3
## - `card2_American Express` 1     67.0 5298.9 1503.6
## - `card_American Express` 1     95.3 5327.1 1522.2
## - carditems          1    1050.4 6282.3 2099.4
## - card2spent         1   16611.8 21843.6 6461.0
## - cardspent          1   19217.7 24449.5 6855.5
##
## Step: AIC=1459.63
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_50-64` + `agecat_35-49` + employ_10 +
##   employ_11 + employ_8 + employ_2 + employ_18 + employ_28 +
##   employ_26 + employ_7 + employ_9 + employ_20 + `carown_N/A` +
##   `card_American Express` + cardtype_Other + card2_Mastercard +
##   `card2_American Express` + card2_Visa + churn_No + voice_No
##
##           Df Sum of Sq    RSS    AIC
## - employ_7          1      1.1 5233.8 1458.3
## - employ_10         1      1.4 5234.1 1458.5
## - employ_11         1      1.6 5234.4 1458.7
## - employ_28         1      2.1 5234.9 1459.0
## - employ_8          1      2.2 5234.9 1459.1
## - employ_26         1      2.4 5235.2 1459.3

```

```

## - ed 1 2.9 5235.6 1459.5
## - employ_2 1 3.0 5235.8 1459.6
## <none> 5232.8 1459.6
## - employ_18 1 3.1 5235.9 1459.7
## - card2_Visa 1 3.2 5236.0 1459.8
## - employ_9 1 3.2 5236.0 1459.8
## - employ_20 1 4.0 5236.8 1460.3
## + employ_35 1 0.9 5231.8 1461.0
## + `agecat_>65` 1 0.9 5231.9 1461.0
## - churn_No 1 5.1 5237.9 1461.0
## + `spousedcat_College degree` 1 0.8 5231.9 1461.1
## - cardtype_Other 1 5.2 5238.0 1461.1
## + employ_34 1 0.6 5232.1 1461.2
## + pager_No 1 0.6 5232.2 1461.2
## - `carown_N/A` 1 5.5 5238.3 1461.3
## + card2_Discover 1 0.4 5232.4 1461.4
## + employ_27 1 0.3 5232.5 1461.4
## + employ_15 1 0.3 5232.5 1461.4
## + employ_38 1 0.2 5232.6 1461.5
## + employ_1 1 0.1 5232.7 1461.6
## + cardtype_Platinum 1 0.0 5232.7 1461.6
## + employ_12 1 0.0 5232.8 1461.6
## - voice_No 1 6.8 5239.6 1462.2
## - card2_Mastercard 1 8.2 5240.9 1463.1
## - `agecat_50-64` 1 12.7 5245.5 1466.1
## - `agecat_35-49` 1 27.4 5260.2 1475.9
## - lncreddebt 1 51.2 5284.0 1491.7
## - `card2_American Express` 1 67.2 5299.9 1502.3
## - `card_American Express` 1 95.6 5328.4 1521.0
## - carditems 1 1051.0 6283.7 2098.2
## - card2spent 1 16612.1 21844.8 6459.2
## - cardspent 1 19219.2 24452.0 6853.8
##
## Step: AIC=1458.34
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
## card2spent + `agecat_50-64` + `agecat_35-49` + employ_10 +
## employ_11 + employ_8 + employ_2 + employ_18 + employ_28 +
## employ_26 + employ_9 + employ_20 + `carown_N/A` + `card_American Express` +
## cardtype_Other + card2_Mastercard + `card2_American Express` +
## card2_Visa + churn_No + voice_No
##
## Df Sum of Sq RSS AIC
## - employ_10 1 1.5 5235.3 1457.3
## - employ_11 1 1.8 5235.6 1457.5
## - employ_28 1 2.2 5236.0 1457.8
## - employ_8 1 2.4 5236.2 1457.9
## - employ_26 1 2.5 5236.3 1458.0
## - ed 1 2.9 5236.7 1458.3
## <none> 5233.8 1458.3
## - card2_Visa 1 3.2 5237.1 1458.5
## - employ_2 1 3.2 5237.1 1458.5
## - employ_18 1 3.3 5237.1 1458.5
## - employ_9 1 3.5 5237.3 1458.7
## - employ_20 1 4.2 5238.0 1459.1

```

```

## + employ_7          1      1.1 5232.8 1459.6
## + employ_35         1      1.0 5232.9 1459.7
## + `spousedcat_College degree` 1      0.9 5232.9 1459.7
## - churn_No         1      5.1 5239.0 1459.8
## + `agecat_>65`      1      0.8 5233.0 1459.8
## - cardtype_Other    1      5.3 5239.1 1459.9
## + employ_34         1      0.7 5233.2 1459.9
## + pager_No         1      0.6 5233.2 1459.9
## - `carown_N/A`      1      5.4 5239.2 1459.9
## + employ_27         1      0.4 5233.5 1460.1
## + employ_15         1      0.3 5233.5 1460.1
## + card2_Discover    1      0.3 5233.5 1460.1
## + employ_38         1      0.2 5233.7 1460.2
## + employ_1          1      0.1 5233.7 1460.2
## + cardtype_Platinum 1      0.0 5233.8 1460.3
## + employ_12         1      0.0 5233.8 1460.3
## - voice_No         1      6.8 5240.6 1460.9
## - card2_Mastercard  1      8.2 5242.1 1461.8
## - `agecat_50-64`    1     13.1 5246.9 1465.1
## - `agecat_35-49`    1     28.3 5262.1 1475.2
## - lncreddebt        1     51.1 5285.0 1490.4
## - `card2_American Express` 1     67.3 5301.2 1501.1
## - `card_American Express` 1     96.3 5330.1 1520.1
## - carditems         1    1049.9 6283.7 2096.2
## - card2spent        1   16612.4 21846.3 6457.4
## - cardspent         1   19224.4 24458.2 6852.7
##
## Step: AIC=1457.35
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_50-64` + `agecat_35-49` + employ_11 +
##   employ_8 + employ_2 + employ_18 + employ_28 + employ_26 +
##   employ_9 + employ_20 + `carown_N/A` + `card_American Express` +
##   cardtype_Other + card2_Mastercard + `card2_American Express` +
##   card2_Visa + churn_No + voice_No
##
##
##           Df Sum of Sq      RSS      AIC
## - employ_11      1      1.6 5237.0 1456.4
## - employ_28      1      2.1 5237.5 1456.8
## - employ_8       1      2.2 5237.5 1456.8
## - employ_26      1      2.4 5237.8 1457.0
## - ed             1      2.8 5238.1 1457.2
## <none>                    5235.3 1457.3
## - employ_2       1      3.0 5238.4 1457.4
## - card2_Visa     1      3.1 5238.5 1457.4
## - employ_18      1      3.1 5238.5 1457.4
## - employ_9       1      3.2 5238.6 1457.5
## - employ_20      1      4.0 5239.4 1458.0
## + employ_10      1      1.5 5233.8 1458.3
## + employ_7       1      1.2 5234.1 1458.5
## + employ_35      1      0.9 5234.4 1458.7
## + `agecat_>65`    1      0.9 5234.4 1458.7
## + `spousedcat_College degree` 1      0.8 5234.5 1458.8
## - churn_No      1      5.3 5240.6 1458.9
## - cardtype_Other 1      5.3 5240.6 1458.9

```

```

## + pager_No          1      0.7  5234.7 1458.9
## + employ_34         1      0.6  5234.7 1458.9
## - `carown_N/A`      1      5.6  5241.0 1459.1
## + card2_Discover    1      0.3  5235.0 1459.1
## + employ_27         1      0.3  5235.0 1459.1
## + employ_15         1      0.3  5235.1 1459.2
## + employ_38         1      0.2  5235.2 1459.2
## + employ_1          1      0.1  5235.3 1459.3
## + cardtype_Platinum 1      0.1  5235.3 1459.3
## + employ_12         1      0.0  5235.3 1459.3
## - voice_No          1      6.7  5242.0 1459.8
## - card2_Mastercard   1      8.2  5243.5 1460.8
## - `agecat_50-64`    1     12.5  5247.8 1463.7
## - `agecat_35-49`    1     27.3  5262.6 1473.5
## - lncreddebt        1     51.5  5286.8 1489.6
## - `card2_American Express` 1    67.7  5303.1 1500.3
## - `card_American Express` 1    96.3  5331.7 1519.2
## - carditems         1    1056.5  6291.8 2098.7
## - card2spent        1   16617.2 21852.5 6456.4
## - cardspent         1   19225.5 24460.9 6851.1
##
## Step: AIC=1456.42
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_50-64` + `agecat_35-49` + employ_8 +
##   employ_2 + employ_18 + employ_28 + employ_26 + employ_9 +
##   employ_20 + `carown_N/A` + `card_American Express` + cardtype_Other +
##   card2_Mastercard + `card2_American Express` + card2_Visa +
##   churn_No + voice_No
##
##
##           Df Sum of Sq    RSS    AIC
## - employ_8          1      2.0  5238.9 1455.7
## - employ_28         1      2.0  5239.0 1455.8
## - employ_26         1      2.3  5239.3 1456.0
## - employ_2          1      2.8  5239.7 1456.3
## - ed                1      2.8  5239.7 1456.3
## - employ_9          1      3.0  5239.9 1456.4
## <none>                5237.0 1456.4
## - employ_18         1      3.0  5239.9 1456.4
## - card2_Visa        1      3.1  5240.1 1456.5
## - employ_20         1      3.8  5240.8 1457.0
## + employ_11         1      1.6  5235.3 1457.3
## + employ_7          1      1.4  5235.6 1457.5
## + employ_10         1      1.3  5235.6 1457.5
## + `agecat_>65`      1      1.1  5235.8 1457.7
## + employ_35         1      0.9  5236.0 1457.8
## - cardtype_Other    1      5.1  5242.1 1457.8
## + `spousedcat_College degree` 1      0.8  5236.2 1457.9
## + pager_No          1      0.6  5236.3 1458.0
## + employ_34         1      0.6  5236.3 1458.0
## - churn_No          1      5.6  5242.6 1458.2
## + card2_Discover    1      0.3  5236.6 1458.2
## - `carown_N/A`      1      5.7  5242.6 1458.2
## + employ_27         1      0.3  5236.7 1458.2
## + employ_15         1      0.2  5236.7 1458.3

```

```

## + employ_38          1      0.2  5236.8 1458.3
## + employ_1           1      0.1  5236.9 1458.4
## + cardtype_Platinum  1      0.1  5236.9 1458.4
## + employ_12          1      0.0  5237.0 1458.4
## - voice_No           1      6.8  5243.7 1458.9
## - card2_Mastercard    1      8.2  5245.1 1459.9
## - `agecat_50-64`      1     12.0  5248.9 1462.4
## - `agecat_35-49`      1     26.4  5263.3 1472.0
## - lncreddebt         1     51.1  5288.0 1488.4
## - `card2_American Express` 1     67.9  5304.8 1499.5
## - `card_American Express` 1     95.9  5332.9 1517.9
## - carditems          1    1054.9  6291.8 2096.7
## - card2spent         1   16615.6 21852.6 6454.4
## - cardspent          1   19272.8 24509.8 6856.1
##
## Step:  AIC=1455.74
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_50-64` + `agecat_35-49` + employ_2 +
##   employ_18 + employ_28 + employ_26 + employ_9 + employ_20 +
##   `carown_N/A` + `card_American Express` + cardtype_Other +
##   card2_Mastercard + `card2_American Express` + card2_Visa +
##   churn_No + voice_No
##
##
##           Df Sum of Sq    RSS    AIC
## - employ_28      1      2.0  5240.9 1455.1
## - employ_26      1      2.2  5241.2 1455.2
## - employ_2       1      2.5  5241.4 1455.4
## - ed             1      2.7  5241.6 1455.5
## - employ_9       1      2.8  5241.7 1455.6
## - employ_18      1      2.9  5241.8 1455.6
## <none>                    5238.9 1455.7
## - card2_Visa      1      3.0  5242.0 1455.8
## - employ_20       1      3.7  5242.6 1456.2
## + employ_8        1      2.0  5237.0 1456.4
## + employ_7        1      1.5  5237.4 1456.7
## + employ_11       1      1.4  5237.5 1456.8
## + `agecat_>65`    1      1.2  5237.7 1456.9
## + employ_10       1      1.2  5237.7 1456.9
## - cardtype_Other  1      5.1  5244.0 1457.1
## + employ_35       1      0.9  5238.1 1457.2
## + `spousedcat_College degree` 1      0.8  5238.1 1457.2
## + pager_No       1      0.6  5238.3 1457.3
## + employ_34       1      0.6  5238.4 1457.4
## - churn_No       1      5.5  5244.4 1457.4
## - `carown_N/A`    1      5.6  5244.5 1457.5
## + card2_Discover  1      0.3  5238.6 1457.5
## + employ_27       1      0.3  5238.7 1457.6
## + employ_38       1      0.2  5238.7 1457.6
## + employ_15       1      0.2  5238.8 1457.6
## + cardtype_Platinum 1      0.0  5238.9 1457.7
## + employ_1        1      0.0  5238.9 1457.7
## + employ_12       1      0.0  5238.9 1457.7
## - voice_No       1      6.8  5245.8 1458.3
## - card2_Mastercard 1      8.1  5247.0 1459.1

```

```

## - `agecat_50-64`      1      11.6  5250.5 1461.5
## - `agecat_35-49`      1      25.4  5264.4 1470.7
## - lncreddebt          1      50.6  5289.5 1487.4
## - `card2_American Express` 1      67.7  5306.6 1498.7
## - `card_American Express` 1      96.0  5334.9 1517.3
## - carditems           1    1054.6  6293.5 2095.6
## - card2spent          1   16614.1 21853.0 6452.5
## - cardspent           1   19293.6 24532.5 6857.3
##
## Step:  AIC=1455.06
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_50-64` + `agecat_35-49` + employ_2 +
##   employ_18 + employ_26 + employ_9 + employ_20 + `carown_N/A` +
##   `card_American Express` + cardtype_Other + card2_Mastercard +
##   `card2_American Express` + card2_Visa + churn_No + voice_No
##
##           Df Sum of Sq    RSS    AIC
## - employ_26      1      2.2  5243.1 1454.5
## - employ_2       1      2.4  5243.4 1454.7
## - ed             1      2.5  5243.4 1454.7
## - employ_9       1      2.7  5243.6 1454.9
## - employ_18      1      2.8  5243.7 1454.9
## - card2_Visa     1      2.9  5243.9 1455.0
## <none>                5240.9 1455.1
## - employ_20      1      3.6  5244.5 1455.5
## + employ_28      1      2.0  5238.9 1455.7
## + employ_8       1      1.9  5239.0 1455.8
## + employ_7       1      1.6  5239.3 1456.0
## + `agecat_>65`   1      1.5  5239.5 1456.1
## + employ_11      1      1.4  5239.5 1456.2
## + employ_10      1      1.1  5239.8 1456.3
## + employ_35      1      0.8  5240.1 1456.5
## - cardtype_Other 1      5.1  5246.1 1456.5
## + `spousedcat_College degree` 1      0.8  5240.1 1456.5
## + pager_No       1      0.6  5240.3 1456.6
## + employ_34      1      0.5  5240.4 1456.7
## - `carown_N/A`   1      5.5  5246.4 1456.8
## - churn_No       1      5.6  5246.5 1456.8
## + card2_Discover 1      0.3  5240.6 1456.8
## + employ_27      1      0.3  5240.7 1456.9
## + employ_38      1      0.2  5240.7 1456.9
## + employ_15      1      0.1  5240.8 1457.0
## + cardtype_Platinum 1      0.0  5240.9 1457.0
## + employ_1       1      0.0  5240.9 1457.1
## + employ_12      1      0.0  5240.9 1457.1
## - voice_No       1      6.7  5247.6 1457.5
## - card2_Mastercard 1      7.9  5248.9 1458.4
## - `agecat_50-64` 1     11.8  5252.7 1460.9
## - `agecat_35-49` 1     26.1  5267.0 1470.4
## - lncreddebt     1     50.1  5291.0 1486.3
## - `card2_American Express` 1     68.4  5309.3 1498.4
## - `card_American Express` 1     96.6  5337.5 1517.0
## - carditems      1    1054.2  6295.1 2094.5
## - card2spent     1   16612.1 21853.0 6450.5

```



```

## - cardspent          1    19295.5 24536.4 6855.9
##
## Step:  AIC=1454.52
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##      card2spent + `agecat_50-64` + `agecat_35-49` + employ_2 +
##      employ_18 + employ_9 + employ_20 + `carown_N/A` + `card_American Express` +
##      cardtype_Other + card2_Mastercard + `card2_American Express` +
##      card2_Visa + churn_No + voice_No
##
##              Df Sum of Sq      RSS      AIC
## - employ_2      1         2.3  5245.4 1454.1
## - ed             1         2.3  5245.4 1454.1
## - employ_9       1         2.6  5245.7 1454.3
## - employ_18      1         2.7  5245.8 1454.3
## - card2_Visa     1         2.8  5245.9 1454.4
## <none>                      5243.1 1454.5
## - employ_20      1         3.5  5246.6 1454.9
## + employ_26       1         2.2  5240.9 1455.1
## + employ_28       1         1.9  5241.2 1455.2
## + employ_8        1         1.8  5241.3 1455.3
## + `agecat_>65`    1         1.8  5241.3 1455.3
## + employ_7        1         1.6  5241.4 1455.4
## + employ_11       1         1.3  5241.8 1455.7
## + employ_10       1         1.1  5242.0 1455.8
## + `spousedcat_College degree` 1         0.8  5242.3 1456.0
## + employ_35       1         0.8  5242.3 1456.0
## - cardtype_Other  1         5.3  5248.4 1456.1
## + pager_No       1         0.7  5242.4 1456.1
## + employ_34       1         0.5  5242.6 1456.2
## - `carown_N/A`    1         5.6  5248.7 1456.2
## - churn_No       1         5.6  5248.7 1456.2
## + card2_Discover  1         0.4  5242.7 1456.3
## + employ_27       1         0.2  5242.9 1456.4
## + employ_38       1         0.2  5242.9 1456.4
## + employ_15       1         0.1  5243.0 1456.4
## + cardtype_Platinum 1         0.0  5243.1 1456.5
## + employ_12       1         0.0  5243.1 1456.5
## + employ_1        1         0.0  5243.1 1456.5
## - voice_No       1         6.7  5249.8 1457.0
## - card2_Mastercard 1         8.0  5251.1 1457.9
## - `agecat_50-64`  1        11.6  5254.7 1460.2
## - `agecat_35-49`  1        26.9  5270.0 1470.5
## - lncreddebt      1        49.4  5292.5 1485.3
## - `card2_American Express` 1        68.2  5311.3 1497.8
## - `card_American Express`  1       97.8  5340.9 1517.2
## - carditems       1       1052.3  6295.4 2092.7
## - card2spent      1      16625.3 21868.4 6451.0
## - cardspent       1      19298.5 24541.6 6854.6
##
## Step:  AIC=1454.09
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##      card2spent + `agecat_50-64` + `agecat_35-49` + employ_18 +
##      employ_9 + employ_20 + `carown_N/A` + `card_American Express` +
##      cardtype_Other + card2_Mastercard + `card2_American Express` +

```

```

##      card2_Visa + churn_No + voice_No
##
##              Df Sum of Sq      RSS      AIC
## - employ_9      1      2.4  5247.8 1453.7
## - ed            1      2.5  5248.0 1453.8
## - employ_18     1      2.6  5248.0 1453.8
## - card2_Visa    1      2.9  5248.3 1454.0
## <none>                      5245.4 1454.1
## - employ_20     1      3.3  5248.8 1454.3
## + employ_2      1      2.3  5243.1 1454.5
## + employ_26     1      2.1  5243.4 1454.7
## + employ_7      1      1.9  5243.6 1454.8
## + employ_28     1      1.9  5243.6 1454.8
## + employ_8      1      1.6  5243.8 1455.0
## + `agecat_>65`  1      1.3  5244.1 1455.2
## + employ_11     1      1.1  5244.3 1455.3
## + employ_10     1      0.9  5244.5 1455.5
## + `spousedcat_College degree` 1      0.9  5244.6 1455.5
## + employ_35     1      0.8  5244.7 1455.6
## + pager_No      1      0.7  5244.8 1455.6
## - cardtype_Other 1      5.3  5250.8 1455.7
## - churn_No      1      5.4  5250.8 1455.7
## - `carown_N/A`  1      5.5  5250.9 1455.8
## + employ_34     1      0.5  5245.0 1455.8
## + card2_Discover 1      0.3  5245.1 1455.9
## + employ_38     1      0.2  5245.2 1455.9
## + employ_27     1      0.2  5245.2 1456.0
## + employ_15     1      0.1  5245.4 1456.0
## + cardtype_Platinum 1      0.0  5245.4 1456.1
## + employ_12     1      0.0  5245.4 1456.1
## + employ_1      1      0.0  5245.4 1456.1
## - voice_No      1      6.8  5252.3 1456.7
## - card2_Mastercard 1      8.0  5253.4 1457.4
## - `agecat_50-64` 1     12.1  5257.5 1460.1
## - `agecat_35-49` 1     26.5  5272.0 1469.7
## - lncreddebt    1     50.0  5295.4 1485.3
## - `card2_American Express` 1     68.7  5314.2 1497.6
## - `card_American Express` 1     98.1  5343.6 1517.0
## - carditems     1    1051.6  6297.1 2091.6
## - card2spent    1   16623.0 21868.5 6449.0
## - cardspent     1   19300.1 24545.6 6853.2
##
## Step:  AIC=1453.67
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##      card2spent + `agecat_50-64` + `agecat_35-49` + employ_18 +
##      employ_20 + `carown_N/A` + `card_American Express` + cardtype_Other +
##      card2_Mastercard + `card2_American Express` + card2_Visa +
##      churn_No + voice_No
##
##              Df Sum of Sq      RSS      AIC
## - employ_18      1      2.4  5250.3 1453.3
## - ed            1      2.5  5250.3 1453.3
## - card2_Visa     1      3.0  5250.8 1453.7
## <none>                      5247.8 1453.7

```

```

## - employ_20          1      3.2 5251.0 1453.8
## + employ_9           1      2.4 5245.4 1454.1
## + employ_2           1      2.1 5245.7 1454.3
## + employ_7           1      2.1 5245.7 1454.3
## + employ_26          1      2.0 5245.8 1454.3
## + employ_28          1      1.8 5246.0 1454.5
## + `agecat_>65`       1      1.5 5246.3 1454.7
## + employ_8           1      1.4 5246.4 1454.7
## + employ_11          1      1.0 5246.9 1455.0
## + `spousedcat_College degree` 1      0.9 5247.0 1455.1
## + employ_10          1      0.8 5247.0 1455.1
## + employ_35          1      0.8 5247.1 1455.2
## + pager_No          1      0.7 5247.2 1455.2
## - cardtype_Other     1      5.3 5253.2 1455.2
## - churn_No           1      5.5 5253.3 1455.3
## - `carown_N/A`       1      5.5 5253.4 1455.4
## + employ_34          1      0.4 5247.4 1455.4
## + card2_Discover     1      0.4 5247.4 1455.4
## + employ_38          1      0.3 5247.6 1455.5
## + employ_27          1      0.2 5247.6 1455.6
## + employ_15          1      0.1 5247.8 1455.6
## + employ_12          1      0.0 5247.8 1455.6
## + cardtype_Platinum  1      0.0 5247.8 1455.6
## + employ_1           1      0.0 5247.8 1455.7
## - voice_No           1      6.8 5254.6 1456.2
## - card2_Mastercard   1      8.1 5255.9 1457.0
## - `agecat_50-64`     1     11.4 5259.2 1459.2
## - `agecat_35-49`     1     25.2 5273.0 1468.4
## - lncreddebt         1     50.2 5298.0 1485.0
## - `card2_American Express` 1     68.0 5315.9 1496.8
## - `card_American Express` 1     98.6 5346.4 1516.8
## - carditems          1    1052.2 6300.0 2091.3
## - card2spent         1   16653.4 21901.3 6452.2
## - cardspent          1   19298.7 24546.5 6851.3
##
## Step: AIC=1453.3
## total_spent_sqrt ~ ed + lncreddebt + carditems + cardspent +
##   card2spent + `agecat_50-64` + `agecat_35-49` + employ_20 +
##   `carown_N/A` + `card_American Express` + cardtype_Other +
##   card2_Mastercard + `card2_American Express` + card2_Visa +
##   churn_No + voice_No
##
##
##           Df Sum of Sq    RSS    AIC
## - ed           1      2.4 5252.6 1452.9
## <none>                5250.3 1453.3
## - card2_Visa     1      3.0 5253.3 1453.3
## - employ_20      1      3.1 5253.3 1453.3
## + employ_18      1      2.4 5247.8 1453.7
## + employ_9       1      2.2 5248.0 1453.8
## + employ_7       1      2.2 5248.1 1453.8
## + employ_2       1      2.0 5248.3 1454.0
## + employ_26      1      1.9 5248.3 1454.0
## + `agecat_>65`   1      1.8 5248.4 1454.1
## + employ_28      1      1.8 5248.5 1454.1

```

```

## + employ_8          1      1.3 5248.9 1454.4
## + employ_11         1      0.9 5249.4 1454.7
## + `spousedcat_College degree` 1      0.8 5249.4 1454.7
## + employ_35         1      0.7 5249.5 1454.8
## + employ_10         1      0.7 5249.5 1454.8
## + pager_No         1      0.7 5249.6 1454.8
## - `carown_N/A`      1      5.4 5255.7 1454.9
## - cardtype_Other    1      5.4 5255.7 1454.9
## + card2_Discover     1      0.4 5249.8 1455.0
## + employ_34         1      0.4 5249.8 1455.0
## - churn_No         1      5.7 5256.0 1455.1
## + employ_38         1      0.3 5250.0 1455.1
## + employ_27         1      0.2 5250.1 1455.2
## + employ_12         1      0.1 5250.2 1455.3
## + cardtype_Platinum 1      0.0 5250.2 1455.3
## + employ_1          1      0.0 5250.2 1455.3
## + employ_15         1      0.0 5250.2 1455.3
## - voice_No         1      6.8 5257.1 1455.8
## - card2_Mastercard   1      7.8 5258.1 1456.5
## - `agecat_50-64`    1     10.9 5261.2 1458.6
## - `agecat_35-49`    1     25.2 5275.5 1468.1
## - lncreddebt        1     50.0 5300.2 1484.4
## - `card2_American Express` 1     68.2 5318.5 1496.5
## - `card_American Express` 1     98.2 5348.5 1516.2
## - carditems         1    1053.0 6303.2 2091.0
## - card2spent        1   16660.2 21910.4 6451.7
## - cardspent         1   19296.3 24546.6 6849.3
##
## Step: AIC=1452.87
## total_spent_sqrt ~ lncreddebt + carditems + cardspent + card2spent +
##   `agecat_50-64` + `agecat_35-49` + employ_20 + `carown_N/A` +
##   `card_American Express` + cardtype_Other + card2_Mastercard +
##   `card2_American Express` + card2_Visa + churn_No + voice_No
##
##           Df Sum of Sq    RSS    AIC
## <none>                5252.6 1452.9
## - employ_20          1      3.0 5255.6 1452.9
## - card2_Visa         1      3.1 5255.7 1452.9
## + ed                 1      2.4 5250.3 1453.3
## + employ_18          1      2.3 5250.3 1453.3
## + employ_7           1      2.2 5250.4 1453.4
## + employ_9           1      2.2 5250.4 1453.4
## + employ_2           1      2.2 5250.5 1453.4
## + employ_26          1      1.8 5250.8 1453.6
## + employ_28          1      1.6 5251.0 1453.8
## + `agecat_>65`       1      1.6 5251.0 1453.8
## - churn_No          1      4.6 5257.2 1453.9
## + employ_8           1      1.2 5251.4 1454.1
## + pager_No          1      1.1 5251.5 1454.2
## + employ_11          1      0.9 5251.7 1454.3
## - voice_No          1      5.1 5257.7 1454.3
## + card2_Discover     1      0.7 5251.9 1454.4
## + employ_35          1      0.6 5252.0 1454.4
## + employ_10          1      0.6 5252.0 1454.4

```

```
## - `carown_N/A` 1 5.4 5258.0 1454.5
## + `spousedcat_College degree` 1 0.3 5252.3 1454.6
## + employ_34 1 0.3 5252.3 1454.6
## - cardtype_Other 1 5.7 5258.3 1454.7
## + employ_38 1 0.3 5252.3 1454.7
## + employ_27 1 0.2 5252.5 1454.8
## + employ_12 1 0.1 5252.5 1454.8
## + cardtype_Platinum 1 0.1 5252.6 1454.8
## + employ_15 1 0.0 5252.6 1454.9
## + employ_1 1 0.0 5252.6 1454.9
## - card2_Mastercard 1 8.0 5260.6 1456.2
## - `agecat_50-64` 1 11.1 5263.7 1458.3
## - `agecat_35-49` 1 24.7 5277.3 1467.3
## - lncreddebt 1 48.4 5301.0 1483.0
## - `card2_American Express` 1 66.2 5318.9 1494.7
## - `card_American Express` 1 96.0 5348.7 1514.3
## - carditems 1 1053.0 6305.7 2090.4
## - card2spent 1 16685.7 21938.3 6454.2
## - cardspent 1 19297.1 24549.7 6847.8
```

```
##
```

```
## Call:
```

```
## lm(formula = total_spent_sqrt ~ lncreddebt + carditems + cardspent +
## card2spent + `agecat_50-64` + `agecat_35-49` + employ_20 +
## `carown_N/A` + `card_American Express` + cardtype_Other +
## card2_Mastercard + `card2_American Express` + card2_Visa +
## churn_No + voice_No, data = Dev)
```

```
##
```

```
## Coefficients:
```

```
## (Intercept) 9.61480 0.10063
## carditems 0.20976 0.01760
## card2spent 0.02188 0.14611
## `agecat_35-49` 0.20964 -0.22938
## `carown_N/A` -0.13242 0.48074
## cardtype_Other 0.09432 -0.12687
## `card2_American Express` 0.45245 -0.08044
## churn_No -0.08618 -0.08570
```

```
# Model given after stepwise regression
```

```
fit3 <- lm(formula = total_spent_sqrt ~ ed + lncreddebt + carditems +
cardspent + card2spent + `agecat_50-64` + `agecat_35-49` +
employ_27 + employ_2 + employ_18 + employ_20 + employ_35 +
employ_38 + `spousedcat_College degree` + `card_American Express` +
cardtype_Other + card2_Discover + card2_Mastercard + `card2_American Express` +
card2_Visa + churn_No + voice_No, data = Dev)
```

```
summary(fit3)
```

```
##
## Call:
## lm(formula = total_spent_sqrt ~ ed + lncreddebt + carditems +
##     cardspent + card2spent + `agecat_50-64` + `agecat_35-49` +
##     employ_27 + employ_2 + employ_18 + employ_20 + employ_35 +
##     employ_38 + `spousedcat_College degree` + `card_American Express` +
##     cardtype_Other + card2_Discover + card2_Mastercard + `card2_American Express` +
##     card2_Visa + churn_No + voice_No, data = Dev)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -7.1074 -0.5386  0.2799  0.8329  2.3786
##
## Coefficients:
##              Estimate Std. Error t value
## (Intercept)      9.8121837   0.1608975  60.984
## ed              -0.0096017   0.0073155  -1.313
## lncreddebt       0.1036246   0.0178974   5.790
## carditems        0.2091833   0.0079377  26.353
## cardspent        0.0176037   0.0001557 113.046
## card2spent       0.0218613   0.0002082 104.979
## `agecat_50-64`   0.1436550   0.0540743   2.657
## `agecat_35-49`   0.2122901   0.0520915   4.075
## employ_27       -0.0918786   0.2342787  -0.392
## employ_2        -0.1005082   0.0847328  -1.186
## employ_18       -0.2148387   0.1692938  -1.269
## employ_20       -0.2303926   0.1623446  -1.419
## employ_35       -0.2633954   0.3725225  -0.707
## employ_38        0.1232113   0.3302258   0.373
## `spousedcat_College degree` 0.0599422   0.0791880   0.757
## `card_American Express`    0.4936784   0.0618364   7.984
## cardtype_Other    0.0891504   0.0485091   1.838
## card2_Discover   -0.0542003   0.0924477  -0.586
## card2_Mastercard -0.1728031   0.0882132  -1.959
## `card2_American Express`    0.4172470   0.0964420   4.326
## card2_Visa       -0.1214151   0.0890886  -1.363
## churn_No        -0.1000348   0.0501904  -1.993
## voice_No        -0.0966060   0.0486506  -1.986
##
##              Pr(>|t|)
## (Intercept) < 0.0000000000000002 ***
## ed          0.18943
## lncreddebt  0.00000000766740541 ***
## carditems  < 0.0000000000000002 ***
## cardspent  < 0.0000000000000002 ***
## card2spent < 0.0000000000000002 ***
## `agecat_50-64` 0.00793 **
## `agecat_35-49` 0.00004697653193402 ***
## employ_27      0.69495
## employ_2       0.23563
## employ_18      0.20452
## employ_20      0.15594
## employ_35      0.47958
## employ_38      0.70909
## `spousedcat_College degree` 0.44912
```

```
## `card_American Express`      0.00000000000000191 ***
## cardtype_Other                0.06618 .
## card2_Discover                0.55772
## card2_Mastercard              0.05020 .
## `card2_American Express`     0.00001558252915094 ***
## card2_Visa                    0.17302
## churn_No                      0.04633 *
## voice_No                      0.04714 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.229 on 3477 degrees of freedom
## Multiple R-squared:  0.9665, Adjusted R-squared:  0.9662
## F-statistic: 4554 on 22 and 3477 DF, p-value: < 0.00000000000000022
```

This model is further perfected

```
fit4 <- lm(formula = total_spent_sqrt ~ ed + lncreddebt + carditems +
  cardspent + card2spent + `agecat_50-64` + `agecat_35-49` +
  employ_27 + employ_20 + employ_35 +
  employ_38 + `spousedcat_College degree` + `card_American Express` +
  cardtype_Other + card2_Mastercard + `card2_American Express` +
  card2_Visa + churn_No + voice_No, data = Dev)

summary(fit4)

##
## Call:
## lm(formula = total_spent_sqrt ~ ed + lncreddebt + carditems +
##   cardspent + card2spent + `agecat_50-64` + `agecat_35-49` +
##   employ_27 + employ_20 + employ_35 + employ_38 + `spousedcat_College degree` +
##   `card_American Express` + cardtype_Other + card2_Mastercard +
##   `card2_American Express` + card2_Visa + churn_No + voice_No,
##   data = Dev)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -7.0997 -0.5428  0.2811  0.8330  2.3815
##
## Coefficients:
##              Estimate Std. Error t value
## (Intercept)    9.7730615   0.1513974   64.552
## ed             -0.0102060   0.0072601   -1.406
## lncreddebt      0.1035349   0.0178796    5.791
## carditems       0.2091921   0.0079376   26.355
## cardspent       0.0176020   0.0001557  113.041
## card2spent      0.0218646   0.0002082  105.034
## `agecat_50-64`  0.1432748   0.0539414    2.656
## `agecat_35-49`  0.2107877   0.0520674    4.048
## employ_27      -0.0795043   0.2341763   -0.340
## employ_20      -0.2195111   0.1622356   -1.353
## employ_35      -0.2518119   0.3724794   -0.676
## employ_38       0.1313887   0.3301675    0.398
## `spousedcat_College degree` 0.0601314   0.0791876    0.759
## `card_American Express` 0.4868521   0.0607292    8.017
```

```
## cardtype_Other          0.0896234  0.0484950  1.848
## card2_Mastercard       -0.1302023  0.0551274 -2.362
## `card2_American Express` 0.4591346  0.0687865  6.675
## card2_Visa             -0.0814766  0.0560996 -1.452
## churn_No               -0.1013564  0.0501444 -2.021
## voice_No               -0.0981436  0.0486394 -2.018
##                          Pr(>|t|)
## (Intercept)            < 0.0000000000000002 ***
## ed                     0.15988
## lncreddebt             0.00000000763240270 ***
## carditems              < 0.0000000000000002 ***
## cardspent              < 0.0000000000000002 ***
## card2spent             < 0.0000000000000002 ***
## `agecat_50-64`         0.00794 **
## `agecat_35-49`         0.00005269935624220 ***
## employ_27              0.73425
## employ_20              0.17613
## employ_35              0.49906
## employ_38              0.69069
## `spousedcat_College degree` 0.44769
## `card_American Express` 0.00000000000000147 ***
## cardtype_Other         0.06467 .
## card2_Mastercard        0.01824 *
## `card2_American Express` 0.00000000002870199 ***
## card2_Visa             0.14649
## churn_No               0.04333 *
## voice_No               0.04369 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.229 on 3480 degrees of freedom
## Multiple R-squared:  0.9664, Adjusted R-squared:  0.9662
## F-statistic: 5272 on 19 and 3480 DF, p-value: < 0.00000000000000022
```

The VIF is being studied for this model

```
library(car)
```

```
## Loading required package: carData
##
## Attaching package: 'car'
## The following object is masked from 'package:DescTools':
##
##     Recode
##
## The following object is masked from 'package:dplyr':
##
##     recode
```

```
(VIF <- vif(fit4))
```

```
##              ed              lncreddebt
##      1.269992              1.142734
##      carditems              cardspent
```



```
##          1.632949          2.750462
##          card2spent          `agecat_50-64`
##          1.798863          1.211168
##          `agecat_35-49`          employ_27
##          1.165784          1.008946
##          employ_20          employ_35
##          1.011285          1.007726
##          employ_38 `spousedcat_College degree`
##          1.006858          1.062990
##          `card_American Express`          cardtype_Other
##          1.356257          1.003342
##          card2_Mastercard          `card2_American Express`
##          1.425677          1.470036
##          card2_Visa          churn_No
##          1.405798          1.096339
##          voice_No
##          1.148020
```

```
# VIF of all variables into consideration are below 5
(tolerance <- 1/VIF)
```

```
##          ed          lncreddebt
##          0.7874064          0.8750942
##          carditems          cardspent
##          0.6123891          0.3635753
##          card2spent          `agecat_50-64`
##          0.5559068          0.8256494
##          `agecat_35-49`          employ_27
##          0.8577921          0.9911336
##          employ_20          employ_35
##          0.9888412          0.9923334
##          employ_38 `spousedcat_College degree`
##          0.9931886          0.9407423
##          `card_American Express`          cardtype_Other
##          0.7373231          0.9966689
##          card2_Mastercard          `card2_American Express`
##          0.7014211          0.6802556
##          card2_Visa          churn_No
##          0.7113399          0.9121268
##          voice_No
##          0.8710650
```

```
# The tolerance level for all the levels are above the required 0.2
```

The model is put to test for the accuracy on the model and the testing data

```
dev1 <- data.frame(cbind(Dev, pred_sq = predict(fit4, newdata=Dev)))
dev1$pred <- (dev1$pred_sq)^2
val1 <- data.frame(cbind(Test, pred_sq = predict(fit4, newdata=Test)))
val1$pred <- (val1$pred_sq)^2
```

Now to verify all the measures to see model accuracy

MAPE

```
DescTools::MAPE(x=dev1$pred,dev1$total_spent)
```

```
## [1] 0.1105021
```

```
DescTools::MAPE(x=val1$pred,val1$total_spent)
```

```
## [1] 0.1090822
```

The MAPE value for both are same and are well under the required levels

RMSE

```
DescTools::RMSE(x=dev1$pred,dev1$total_spent)
```

```
## [1] 66.253
```

```
DescTools::RMSE(x=val1$pred,val1$total_spent)
```

```
## [1] 62.54341
```

Given the range of the total spent, RMSE is low and hence the model is a good fit

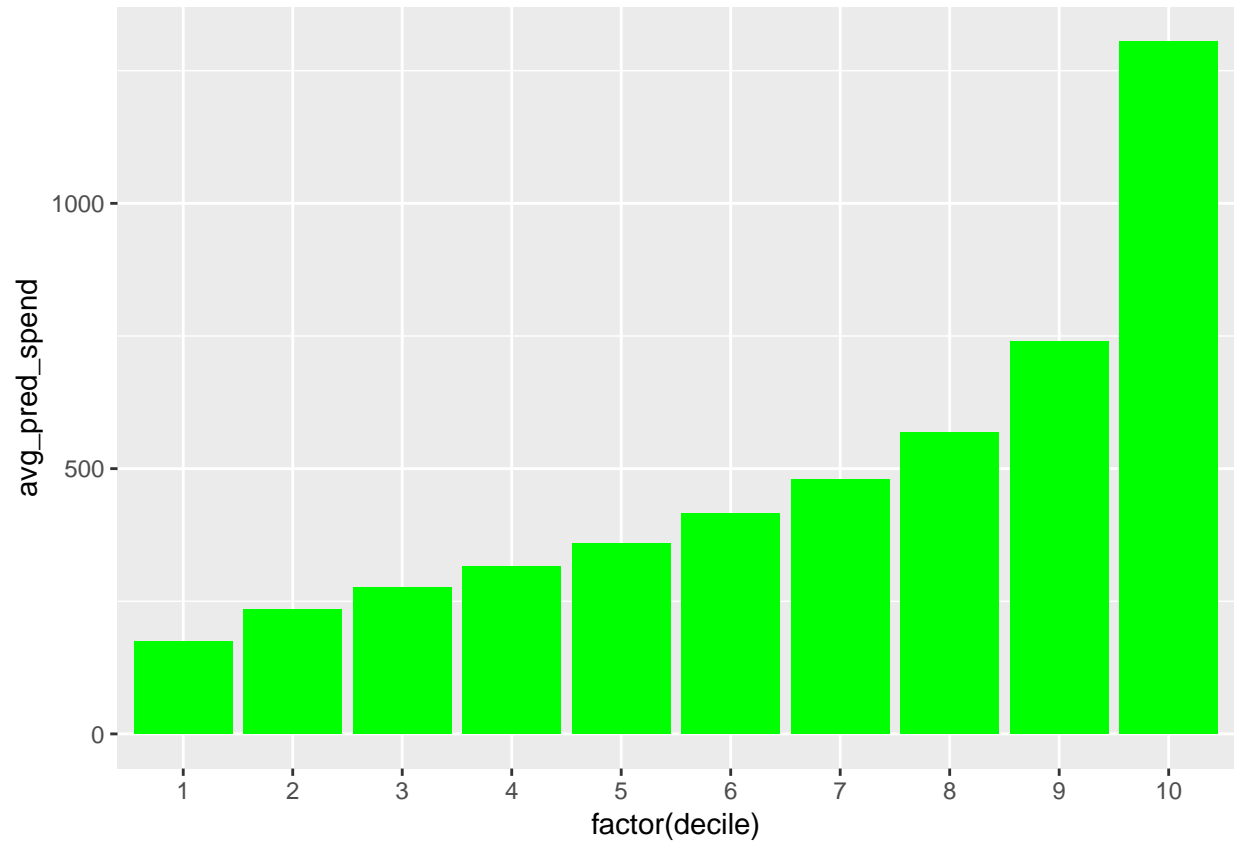
Decile analysis

creating the deciles

```
decLocations <- quantile(val1$pred, probs = seq(0.1,0.9,by=0.1))
val1$decile <- findInterval(val1$pred,c(-Inf,decLocations, Inf))

val_decile <- val1 %>% group_by(decile) %>%
  dplyr::summarise(count = n(),
                   avg_pred_spend = mean(pred),
                   avg_spend = mean(total_spent)
  ) %>%
  dplyr::arrange(desc(decile))

require(ggplot2)
Decile_Plot <- ggplot(val_decile)+aes(x = factor(decile),y = avg_pred_spend) +
  geom_bar(stat = "identity",fill = "green")
plot(Decile_Plot)
```



The decile plot reveals that there is a staircase effect created by the model. Thus, making it a reliable model to use.

Of the factors that influence the balance in a positive way, the top 5 factors are having an American Express card as the primary and secondary card, being in the age category of 35-49 or 50-64 and number of items on primary card. The factors that have a negative impact on the balance value is being with an employer for 35 or 20 years. The negative predictors can be made better.