Assignment #1: German Credit

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Regression Model

```
df <- GermanCredit
df <- df %>% dplyr::select(-Class) # Remove Class variable

full_model <- lm(Amount ~ ., data=df)

# Save and Print Coefficients
full_model_coeff <- full_model$coefficients
full_model_coeff
```

```
##                             (Intercept)                                Duration
##                              6473.24572                              127.22804
##                InstallmentRatePercentage                       ResidenceDuration
##                                -783.07567                               -52.07222
##                                     Age                     NumberExistingCredits
##                                 5.75204                               75.35581
##                   NumberPeopleMaintenance                               Telephone
##                                -198.28236                             -483.36894
##                             ForeignWorker                 CheckingAccountStatus.lt.0
##                                -249.97139                             -104.08052
##           CheckingAccountStatus.0.to.200                CheckingAccountStatus.gt.200
##                                 213.45397                             -614.78718
##               CheckingAccountStatus.none             CreditHistory.NoCredit.AllPaid
##                                       NA                              858.17909
##           CreditHistory.ThisBank.AllPaid                    CreditHistory.PaidDuly
##                                -50.32424                             -15.85221
##                      CreditHistory.Delay                    CreditHistory.Critical
##                                 102.78461                                     NA
##                             Purpose.NewCar                        Purpose.UsedCar
##                                -1757.06185                            -1119.30058
##                Purpose.Furniture.Equipment                 Purpose.Radio.Television
##                                -1836.09216                            -2071.60201
##                 Purpose.DomesticAppliance                        Purpose.Repairs
##                                -2464.06380                            -1707.78133
##                          Purpose.Education                       Purpose.Vacation
##                                -1892.28951                                   NA
##                       Purpose.Retraining                       Purpose.Business
##                                -2209.35799                            -1989.46611
##                             Purpose.Other                SavingsAccountBonds.lt.100
```

```
##                                     NA                                     -327.00664
##          SavingsAccountBonds.100.to.500         SavingsAccountBonds.500.to.1000
##                                -569.23487                                -643.52855
##             SavingsAccountBonds.gt.1000             SavingsAccountBonds.Unknown
##                                -385.98649                                      NA
##                  EmploymentDuration.lt.1               EmploymentDuration.1.to.4
##                                 115.35227                                 51.82530
##                EmploymentDuration.4.to.7                 EmploymentDuration.gt.7
##                                 113.35764                                -163.18910
##           EmploymentDuration.Unemployed       Personal.Male.Divorced.Seperated
##                                     NA                                 480.33678
##                Personal.Female.NotSingle                   Personal.Male.Single
##                                 282.09482                                 730.16723
##           Personal.Male.Married.Widowed                 Personal.Female.Single
##                                     NA                                      NA
##              OtherDebtorsGuarantors.None     OtherDebtorsGuarantors.CoApplicant
##                                 138.71303                                 752.18304
##         OtherDebtorsGuarantors.Guarantor                   Property.RealEstate
##                                     NA                                -840.99813
##                       Property.Insurance                     Property.CarOther
##                                -588.80108                                -570.75237
##                         Property.Unknown           OtherInstallmentPlans.Bank
##                                     NA                                -143.90714
##             OtherInstallmentPlans.Stores           OtherInstallmentPlans.None
##                                -62.89011                                      NA
##                              Housing.Rent                              Housing.Own
##                                 243.68008                                 131.43220
##                           Housing.ForFree              Job.UnemployedUnskilled
##                                     NA                                -1715.11138
##                    Job.UnskilledResident                  Job.SkilledEmployee
##                                -1198.70995                               -1253.90023
## Job.Management.SelfEmp.HighlyQualified
##                                     NA
```

Split into Train/Test Sets and Run Model 1,000 times

```
set.seed(777)

# Create ID to help with splitting into Train/Test
df$id <- 1:nrow(df)

# Initialize empty Data Frame
my_df <- data.frame()

# Run 1,000 Linear models
for(n in 1:1000){

  # Split 63.20% of the data into the train set and the rest into the test set
  train <- df %>% dplyr::sample_frac(0.632)
  test  <- dplyr::anti_join(df, train, by = 'id')
```

```
  # Drop id column before running model since it does not have value
  train$id <- NULL
  test$id  <- NULL

  # Run the linear model on all the independent variables
  model <- lm(Amount ~., data=train)

  # Capture the predictions on the Test / Holdout set
  predictions <- predict(model, test)

  # Save the coefficients, and R-squared for the training and holdout
  save_coeff <- model$coefficients
  save_r2_training <- summary(model)$r.squared
  save_r2_holdout <- cor(test$Amount, predict(model, newdata = test))^2

  con <- c(save_coeff, save_r2_training, save_r2_holdout)
  my_df <- rbind(my_df, con)
}

# Remove ID variable and Amount (dependent) variable
df$id <- NULL
df$Amount <- NULL

# Update Column Names
colnames(my_df)[1] <- "(Intercept)"
colnames(my_df)[2:61] <- names(df)
colnames(my_df)[62] <- "training_r2"
colnames(my_df)[63] <- "holdout_r2"

head(my_df, 3)
```

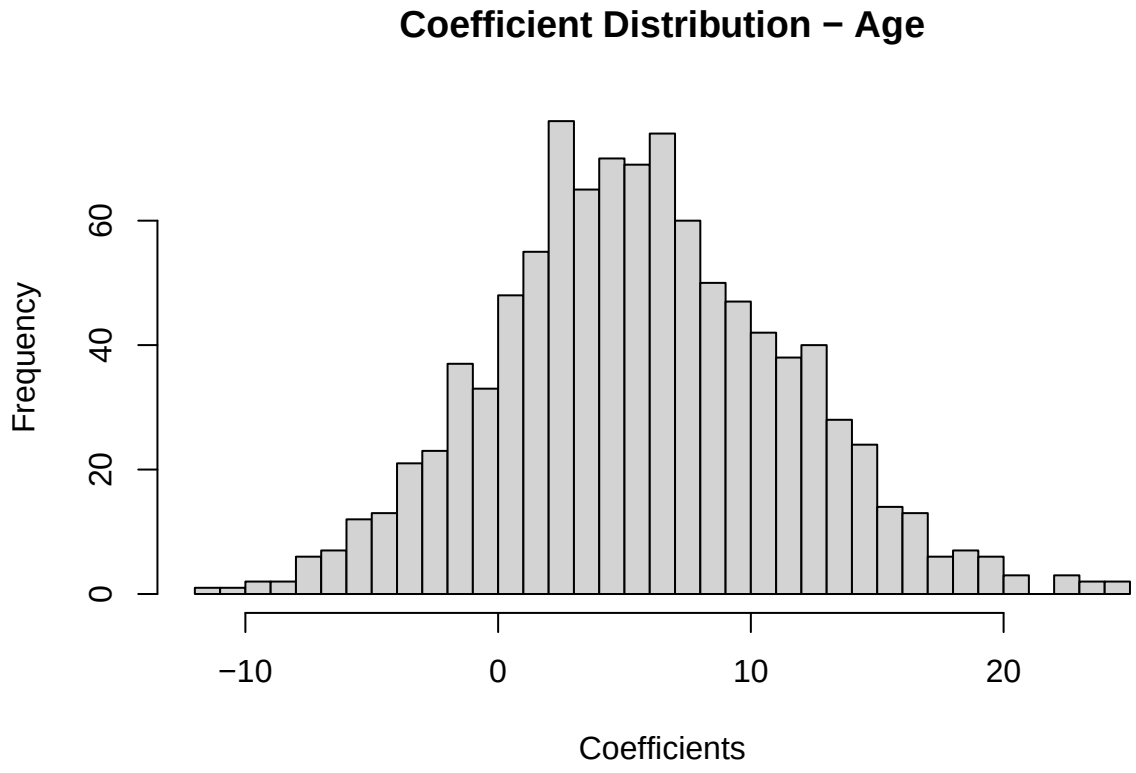
```
##   (Intercept) Duration InstallmentRatePercentage ResidenceDuration        Age
## 1    7053.006 132.5061                 -811.3683          4.879213 -3.3883285
## 2    8742.704 128.5282                 -808.0595       -125.022627  0.4969038
## 3    6213.055 128.2768                 -855.5463         -7.752832 -3.5933384
##   NumberExistingCredits NumberPeopleMaintenance Telephone ForeignWorker
## 1             -64.89621               -276.0670 -361.8853     -332.9213
## 2             117.92245               -111.0212 -513.6035     -139.2039
## 3             159.22881               -217.7662 -372.9430     -196.7809
##   CheckingAccountStatus.lt.0 CheckingAccountStatus.0.to.200
## 1                -145.86101                       220.0945
## 2                 102.85244                       195.0846
## 3                  39.38775                       379.5955
##   CheckingAccountStatus.gt.200 CheckingAccountStatus.none
## 1                    -584.4721                         NA
## 2                    -677.3200                         NA
## 3                    -410.8699                         NA
##   CreditHistory.NoCredit.AllPaid CreditHistory.ThisBank.AllPaid
## 1                       962.4469                     -402.1201
## 2                       715.3007                      127.1241
## 3                       847.2132                     -264.0714
##   CreditHistory.PaidDuly CreditHistory.Delay CreditHistory.Critical
## 1             -325.39323          -248.09909                     NA
```

```
## 2              107.28357           248.44989                      NA
## 3               83.04295           -81.16513                      NA
##   Purpose.NewCar Purpose.UsedCar Purpose.Furniture.Equipment
## 1      -1190.621       -163.0444                   -1110.880
## 2      -3616.351      -2960.3367                   -3900.596
## 3      -2202.571      -1245.5712                   -2258.378
##   Purpose.Radio.Television Purpose.DomesticAppliance Purpose.Repairs
## 1                -1343.701                -2101.464       -1402.828
## 2                -3987.831                -4747.327       -3527.883
## 3                -2402.341                -2819.007       -1916.458
##   Purpose.Education Purpose.Vacation Purpose.Retraining Purpose.Business
## 1         -809.9535               NA          -1437.532        -1149.776
## 2        -3660.1191               NA          -4200.430        -3827.898
## 3        -1971.9619               NA          -3509.607        -2588.997
##   Purpose.Other SavingsAccountBonds.lt.100 SavingsAccountBonds.100.to.500
## 1            NA                  -442.9623                       -636.0945
## 2            NA                  -432.0049                       -633.2180
## 3            NA                  -444.3698                       -320.4523
##   SavingsAccountBonds.500.to.1000 SavingsAccountBonds.gt.1000
## 1                       -813.7547                  -349.6858
## 2                       -499.8858                  -474.0402
## 3                       -798.5119                  -366.0600
##   SavingsAccountBonds.Unknown EmploymentDuration.lt.1 EmploymentDuration.1.to.4
## 1                          NA              -250.82327                -413.26081
## 2                          NA               -79.14711                 -39.77819
## 3                          NA               162.34220                 212.60865
##   EmploymentDuration.4.to.7 EmploymentDuration.gt.7
## 1                -318.16077              -618.95656
## 2                  51.27917               -77.74344
## 3                 281.68776               -37.57796
##   EmploymentDuration.Unemployed Personal.Male.Divorced.Seperated
## 1                            NA                         624.6313
## 2                            NA                         719.7154
## 3                            NA                         678.8079
##   Personal.Female.NotSingle Personal.Male.Single Personal.Male.Married.Widowed
## 1                  333.4951             812.9995                             NA
## 2                  308.9360             714.9203                             NA
## 3                  -31.7201             638.3747                             NA
##   Personal.Female.Single OtherDebtorsGuarantors.None
## 1                     NA                   -88.6265
## 2                     NA                   164.2454
## 3                     NA                   573.1364
##   OtherDebtorsGuarantors.CoApplicant OtherDebtorsGuarantors.Guarantor
## 1                           572.7070                               NA
## 2                           516.7521                               NA
## 3                          1048.1418                               NA
##   Property.RealEstate Property.Insurance Property.CarOther Property.Unknown
## 1           -765.9383          -717.8129         -736.9864               NA
## 2           -725.9376          -507.3184         -430.6413               NA
## 3          -1062.9615          -749.6071         -850.4425               NA
##   OtherInstallmentPlans.Bank OtherInstallmentPlans.Stores
## 1                  -220.58870                   -24.26371
## 2                  -253.11178                  -110.13515
## 3                   -64.04921                    23.08561
```

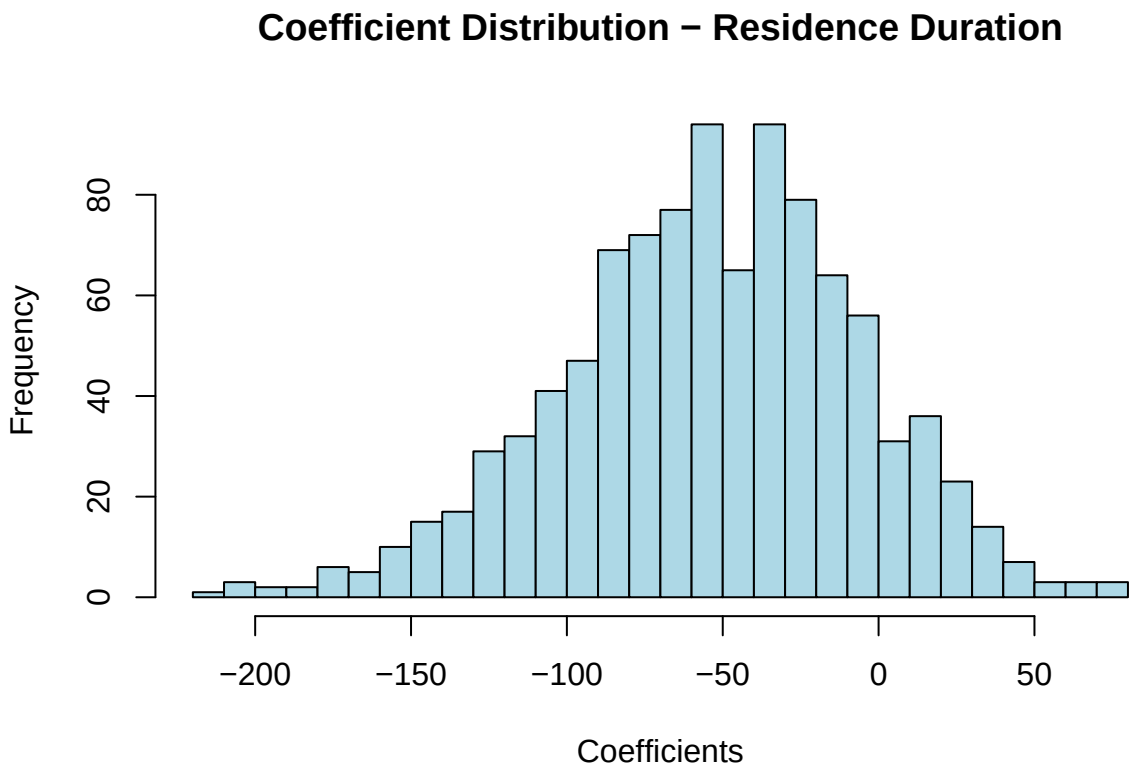
```
##   OtherInstallmentPlans.None Housing.Rent Housing.Own Housing.ForFree
## 1                         NA   232.368137    258.7847             NA
## 2                         NA     8.499965   -170.6788             NA
## 3                         NA   673.179510    764.3539             NA
##   Job.UnemployedUnskilled Job.UnskilledResident Job.SkilledEmployee
## 1                -1402.272             -1144.332           -1258.025
## 2                -1830.999             -1187.417           -1263.488
## 3                -1582.527             -1269.402           -1220.914
##   Job.Management.SelfEmp.HighlyQualified training_r2 holdout_r2
## 1                                     NA   0.6178389  0.5648368
## 2                                     NA   0.6122784  0.5816260
## 3                                     NA   0.6231289  0.5467266
```

Coefficient & R-Squared Distributions

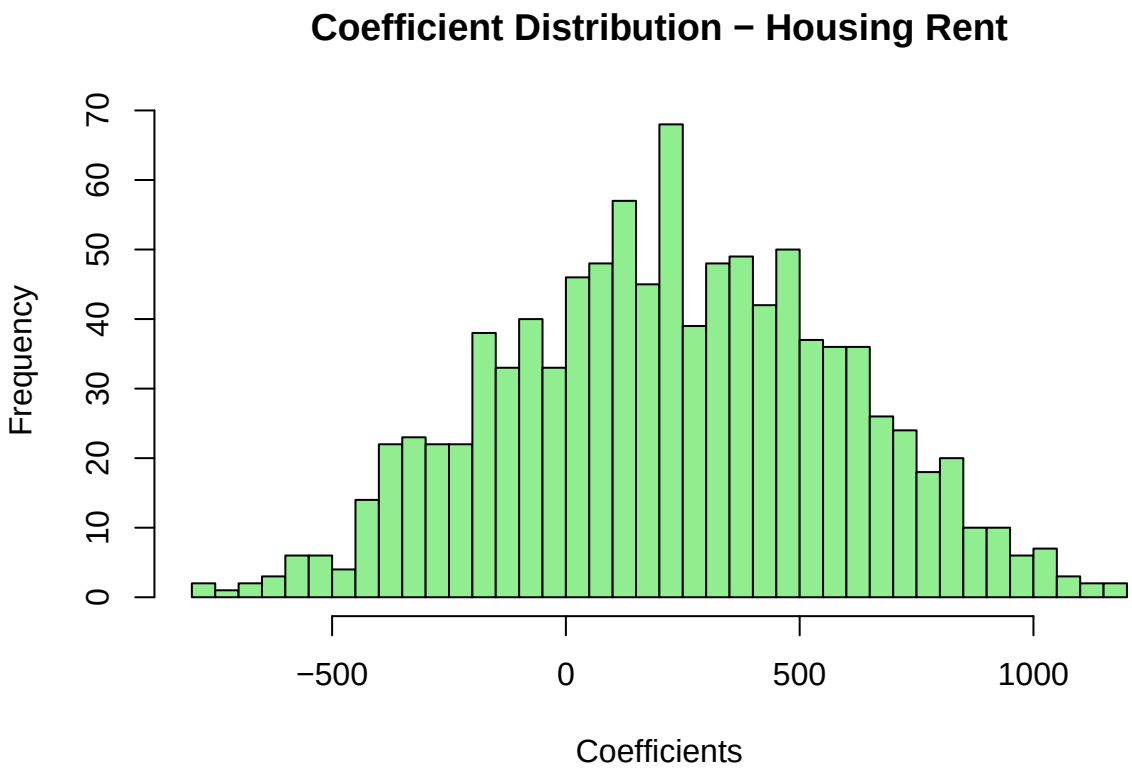
```
hist(my_df$Age,
     breaks=30,
     xlab = "Coefficients", main = "Coefficient Distribution - Age")
```




```
hist(my_df$ResidenceDuration,
     breaks=30,
     xlab = "Coefficients", main = "Coefficient Distribution - Residence Duration", col="lightblue")
```




```
hist(my_df$Housing.Rent,
     breaks=30,
     xlab = "Coefficients", main = "Coefficient Distribution - Housing Rent", col="lightgreen")
```



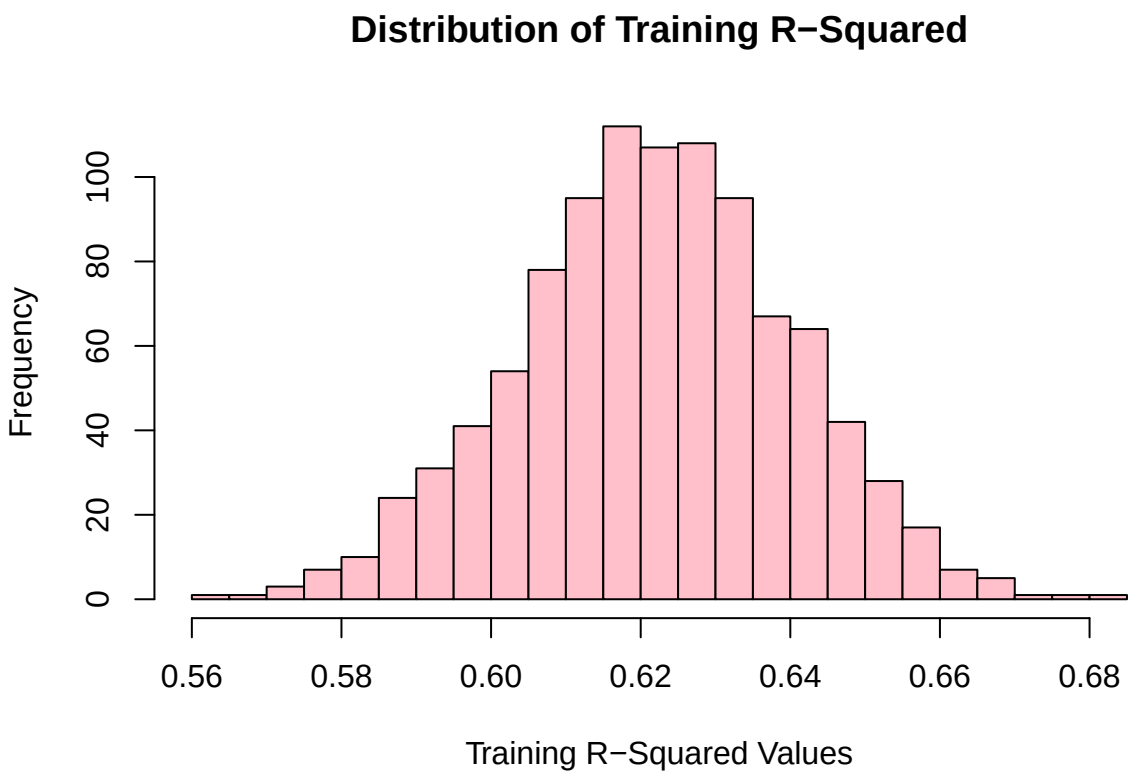
Summary - Interpretation of Above Plots ~ all plots printed above are fairly normally distributed. See individual interpretations here:

Age: the age coefficients are sometimes negatives which is the opposite of what I would normally think. Generally older people have higher credit, so seeing that the model sometimes says a higher age means a lesser loan is surprising. Overall the plot indicates age tends to have a positive impact on the loan amount, i.e., older people get higher loans.

Residence Duration: this coefficient value is mostly negative meaning the longer someone resides in a location, the lower their predicted loan Amount. This may be because wealthier people who can get higher loans tend to move around more and can afford to move to new places. This matches expectations.

Housing Rent: this coefficient value is mostly positive meaning the higher someone's rent the higher their predicted loan amount tends to be. This makes sense is people who can afford more expensive living places will generally be approved for higher loans due to high credit scores and proof of income.

```
hist(my_df$training_r2,
     breaks=30,
     xlab = "Training R-Squared Values", main = "Distribution of Training R-Squared", col="pink")
```




```
mean(my_df$training_r2)
```

```
## [1] 0.6219217
```

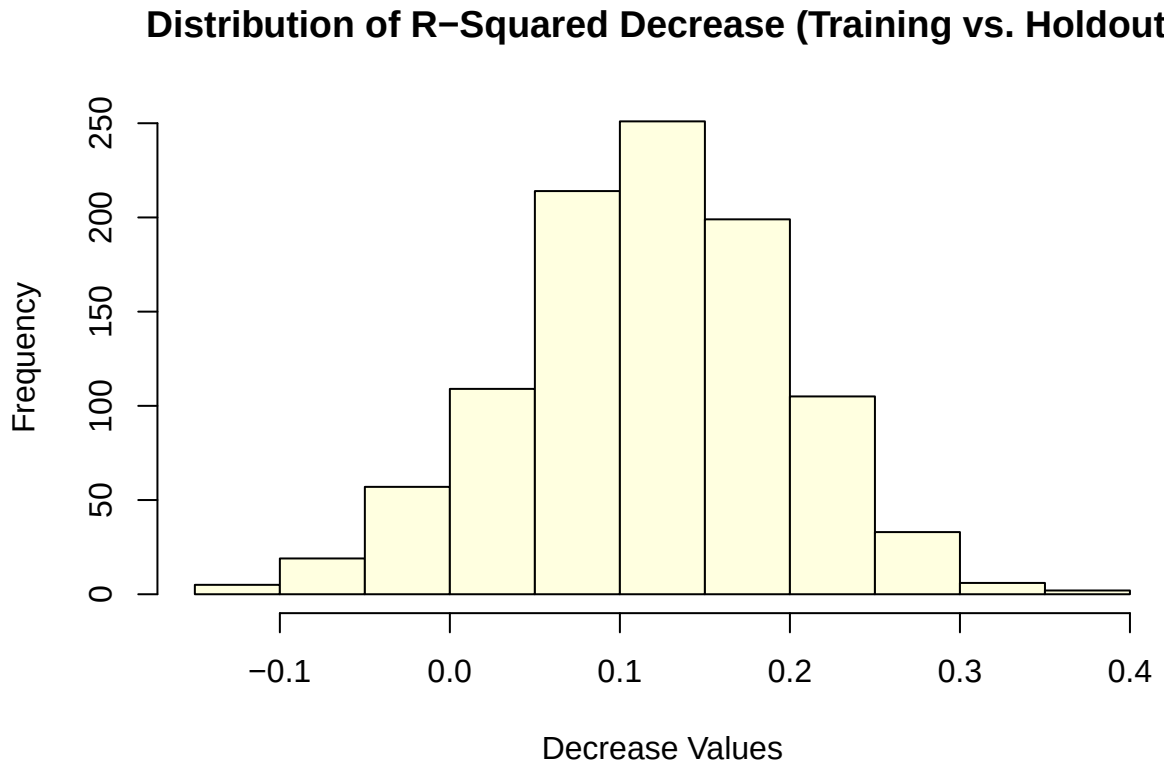
```
median(my_df$training_r2)
```

```
## [1] 0.6221699
```

```
my_df <- my_df %>% mutate(r2_decrease = (training_r2 - holdout_r2)/training_r2)
head(my_df$r2_decrease, 5)
```

```
## [1] 0.08578634 0.05006284 0.12261069 0.26808393 0.02836774
```

```
hist(my_df$r2_decrease,
     breaks=12,
     xlab = "Decrease Values", main = "Distribution of R-Squared Decrease (Training vs. Holdout)",
     col="lightyellow")
```




```
mean(my_df$r2_decrease)
```

```
## [1] 0.1170542
```

```
median(my_df$r2_decrease)
```

```
## [1] 0.1206984
```

```
print(my_df %>% dplyr::select(training_r2, holdout_r2, r2_decrease) %>% head(50))
```

```
##    training_r2 holdout_r2   r2_decrease
## 1    0.6178389  0.5648368  0.0857863355
## 2    0.6122784  0.5816260  0.0500628400
## 3    0.6231289  0.5467266  0.1226106867
## 4    0.6551495  0.4795145  0.2680839314
## 5    0.6012938  0.5842365  0.0283677370
## 6    0.6340567  0.5337269  0.1582346692
## 7    0.6188586  0.5557455  0.1019829975
## 8    0.6164051  0.5536415  0.1018220776
## 9    0.5982695  0.5985234 -0.0004245089
## 10   0.6397308  0.5176429  0.1908426374
## 11   0.6000028  0.5482957  0.0861780538
## 12   0.6037554  0.5803066  0.0388383056
## 13   0.6334589  0.5283196  0.1659765377
```

```
## 14   0.6173947  0.5658332  0.0835147594
## 15   0.6210535  0.5477813  0.1179805443
## 16   0.6106144  0.5530821  0.0942203565
## 17   0.6134021  0.5575521  0.0910496413
## 18   0.6438279  0.5174397  0.1963073107
## 19   0.6049618  0.5835958  0.0353178444
## 20   0.6245379  0.5299596  0.1514372921
## 21   0.5963560  0.6032114 -0.0114955273
## 22   0.6043744  0.5843905  0.0330654064
## 23   0.6218616  0.5506347  0.1145381803
## 24   0.6167813  0.5549219  0.1002938802
## 25   0.5978763  0.6036830 -0.0097121075
## 26   0.6260023  0.5500076  0.1213967820
## 27   0.6255635  0.5432675  0.1315549909
## 28   0.6295040  0.5267499  0.1632301544
## 29   0.6326533  0.5333377  0.1569825844
## 30   0.6428717  0.5112702  0.2047088501
## 31   0.6091231  0.5752858  0.0555508684
## 32   0.6340840  0.5293777  0.1651299750
## 33   0.6421735  0.5131129  0.2009746515
## 34   0.6379048  0.5011755  0.2143410967
## 35   0.6135948  0.5685748  0.0733710006
## 36   0.6117161  0.5764857  0.0575927863
## 37   0.5948481  0.5790292  0.0265931652
## 38   0.6127203  0.5530253  0.0974262573
## 39   0.6190223  0.5429781  0.1228456077
## 40   0.6511310  0.5118781  0.2138631726
## 41   0.5945557  0.6033419 -0.0147776950
## 42   0.6183006  0.5550103  0.1023616403
## 43   0.6289958  0.5381734  0.1443925954
## 44   0.6349317  0.5450295  0.1415934991
## 45   0.6154182  0.5547086  0.0986476804
## 46   0.6166456  0.5515340  0.1055900680
## 47   0.6059274  0.5327837  0.1207137459
## 48   0.5868796  0.6045618 -0.0301291589
## 49   0.6322975  0.5217788  0.1747891788
## 50   0.5928144  0.6132644 -0.0344963997
```

Interpretation:

These plots are also normally distributed and indicate that on average we can expect around a 12% percentage decrease from our training dataset R-squared of 62% to our holdout dataset. This means the model performs slightly worse on the holdout data. This is to be expected because this is unseen data – we just want the model to be able to generalize well, not necessarily have an excellent R-squared value. This is a good result.

```
coefficient_means <- colMeans(my_df)
head(coefficient_means, 5)
```

```
##               (Intercept)                  Duration InstallmentRatePercentage
##                6514.445005                126.992393                -782.770921
##         ResidenceDuration                       Age
```

```
##                -53.757369                   5.662497
```

```
coefficient_sds <- sapply(my_df, sd)
head(coefficient_sds, 5)
```

```
##               (Intercept)                  Duration InstallmentRatePercentage
##                1288.098431                   5.387694                  47.668309
##         ResidenceDuration                       Age
##                  47.748450                   5.836145
```

```
# Difference between coefficient_means and actual model coefficients
bind <- data.frame(cbind(coefficient_means, save_coeff))
bind$abs_raw_diff <- abs(coefficient_means - save_coeff)
bind$percent_diff <- 100*abs(((coefficient_means - save_coeff) / save_coeff))

print(bind %>% na.omit())
```

```
##                                  coefficient_means    save_coeff abs_raw_diff
## (Intercept)                         6514.4450052  6787.3109335   272.865928
## Duration                             126.9923926   121.7024620     5.289931
## InstallmentRatePercentage           -782.7709212  -803.3828621    20.611941
## ResidenceDuration                    -53.7573686    20.1154552    73.872824
## Age                                    5.6624968     1.4118155     4.250681
## NumberExistingCredits                 75.5933144     9.3048900    66.288424
## NumberPeopleMaintenance             -207.9595145  -294.5123347    86.552820
## Telephone                           -478.1912394  -430.0143516    48.176888
## ForeignWorker                       -236.7257922  -174.4323728    62.293419
## CheckingAccountStatus.lt.0          -103.2913906    -0.3607945   102.930596
## CheckingAccountStatus.0.to.200       205.8951983   279.2494699    73.354272
## CheckingAccountStatus.gt.200        -616.6448860  -573.6950070    42.949879
## CreditHistory.NoCredit.AllPaid       849.4984033   508.5678641   340.930539
## CreditHistory.ThisBank.AllPaid       -47.9907468  -459.7257283   411.734981
## CreditHistory.PaidDuly               -15.6668989   -61.1902427    45.523344
## CreditHistory.Delay                  113.9620829   138.9943540    25.032271
## Purpose.NewCar                     -1768.1136034 -2180.1076255   411.994022
## Purpose.UsedCar                    -1131.1941473 -1440.8553893   309.661242
## Purpose.Furniture.Equipment        -1851.4854148 -2295.6493157   444.163901
## Purpose.Radio.Television           -2085.7345008 -2454.9706733   369.236173
## Purpose.DomesticAppliance          -2481.7388581 -2559.0089901    77.270132
## Purpose.Repairs                    -1710.5724217 -1977.8988925   267.326471
## Purpose.Education                  -1907.1014641 -2429.6229301   522.521466
## Purpose.Business                   -1992.6396355 -2597.8420276   605.202392
## SavingsAccountBonds.lt.100          -329.4394441  -334.6707759     5.231332
## SavingsAccountBonds.100.to.500      -564.8601422  -201.3723119   363.487830
## SavingsAccountBonds.500.to.1000     -659.1950634  -769.0039648   109.808901
## SavingsAccountBonds.gt.1000         -386.4586074  -108.6142881   277.844319
## EmploymentDuration.lt.1              114.2590421  -293.0847250   407.343767
## EmploymentDuration.1.to.4             48.4814756   -89.4589353   137.940411
## EmploymentDuration.4.to.7            109.5993845  -200.9872948   310.586679
## EmploymentDuration.gt.7             -159.3121487  -510.3288707   351.016722
## Personal.Male.Divorced.Seperated     480.5116417   503.3091425    22.797501
## Personal.Female.NotSingle            278.5919279   124.8996358   153.692292
## Personal.Male.Single                 735.2182940   892.2249404   157.006646
```

```
## OtherDebtorsGuarantors.None              129.5228933   133.9857097     4.462816
## OtherDebtorsGuarantors.CoApplicant       736.4230085   677.5142604    58.908748
## Property.RealEstate                     -837.7940304  -900.2620942    62.468064
## Property.Insurance                      -590.7038970  -511.6185864    79.085311
## Property.CarOther                       -566.1199297  -605.4682045    39.348275
## OtherInstallmentPlans.Bank              -150.7777877    31.0931649   181.870953
## OtherInstallmentPlans.Stores             -44.9924066   582.1274420   627.119849
## Housing.Rent                             227.0673423   822.5800230   595.512681
## Housing.Own                              108.5780856   583.4525437   474.874458
## Job.UnemployedUnskilled                -1688.5415978 -1857.0267610   168.485163
## Job.UnskilledResident                  -1192.5282121 -1174.7391001    17.789112
## Job.SkilledEmployee                    -1246.9380397 -1141.4595832   105.478456
## training_r2                                0.6219217  6787.3109335  6786.689012
## holdout_r2                                 0.5477035   121.7024620   121.154758
## r2_decrease                                0.1170542  -803.3828621   803.499916
##                                  percent_diff
## (Intercept)                          4.020236
## Duration                             4.346609
## InstallmentRatePercentage            2.565644
## ResidenceDuration                  367.244107
## Age                                301.079107
## NumberExistingCredits              712.404169
## NumberPeopleMaintenance             29.388521
## Telephone                           11.203553
## ForeignWorker                       35.712075
## CheckingAccountStatus.lt.0       28528.869177
## CheckingAccountStatus.0.to.200      26.268366
## CheckingAccountStatus.gt.200         7.486535
## CreditHistory.NoCredit.AllPaid      67.037374
## CreditHistory.ThisBank.AllPaid      89.561005
## CreditHistory.PaidDuly              74.396410
## CreditHistory.Delay                 18.009560
## Purpose.NewCar                      18.897875
## Purpose.UsedCar                     21.491487
## Purpose.Furniture.Equipment         19.348073
## Purpose.Radio.Television            15.040350
## Purpose.DomesticAppliance            3.019533
## Purpose.Repairs                     13.515679
## Purpose.Education                   21.506278
## Purpose.Business                    23.296351
## SavingsAccountBonds.lt.100           1.563128
## SavingsAccountBonds.100.to.500     180.505367
## SavingsAccountBonds.500.to.1000     14.279367
## SavingsAccountBonds.gt.1000        255.808259
## EmploymentDuration.lt.1            138.984987
## EmploymentDuration.1.to.4          154.194112
## EmploymentDuration.4.to.7          154.530504
## EmploymentDuration.gt.7             68.782454
## Personal.Male.Divorced.Seperated     4.529522
## Personal.Female.NotSingle          123.052634
## Personal.Male.Single                17.597204
## OtherDebtorsGuarantors.None          3.330815
## OtherDebtorsGuarantors.CoApplicant   8.694835
## Property.RealEstate                  6.938875
```

```
## Property.Insurance                  15.457865
## Property.CarOther                    6.498818
## OtherInstallmentPlans.Bank         584.922613
## OtherInstallmentPlans.Stores       107.728962
## Housing.Rent                        72.395714
## Housing.Own                         81.390417
## Job.UnemployedUnskilled              9.072845
## Job.UnskilledResident                1.514303
## Job.SkilledEmployee                  9.240665
## training_r2                         99.990837
## holdout_r2                          99.549965
## r2_decrease                        100.014570
```

Calculate Confidence Intervals & Width

```
# Confidence Interval for Rep 1,000 Coefficients -------------------------------
# Transposed dataframe of confidence intervals for each variable
rep_conf <- data.frame(t(sapply(my_df[,1:63], function(x) Rmisc::CI(x, ci=0.95)))) #%>% na.omit()

# Calculate Width
# rep_conf$width <- (rep_conf$upper-rep_conf$lower)*sqrt(0.632)
rep_conf$width <- (rep_conf$upper-rep_conf$lower)*sqrt(0.632)

# MANUAL CHECK ==============================
# Calculate Means
#means <- data.frame(means=sapply(my_df[1:61], function(x) mean(x)))
#n <- 1000
# Calculate Standard Deviation
#std_dev <- data.frame(std_dev=sapply(my_df[1:61], function(x) sd(x)))

#std_error <- std_dev / sqrt(n)
#alpha = 0.025
#degrees_of_freedom = n-1
#t_score = qt(p=alpha/2, df=degrees_of_freedom,lower.tail=F)
#margin_error <- t_score * std_error

#lower_bound_new <- means - margin_error
#upper_bound_new <- means + margin_error

#x <- cbind(lower_bound_new, upper_bound_new) %>% dplyr::rename(lower_new = 1, upper_new = 2)

#margin <- qnorm(0.975)*std
#rep_CI_low_manual <- means - margin
#rep_CI_high_manual <- means + margin
#manual <- cbind(rep_CI_low_manual, rep_CI_high_manual) %>%
#                dplyr::rename(lower_manual = 1, upper_manual = 2)


# ============================

# Reorder columns
rep_conf <- rep_conf %>% select(lower, upper, width)
```

```r
# Keep only valid columns, remove R2 values
rep_conf <- rep_conf[1:61,]

# COMBINE for check
#z <- cbind(rep_conf, manual)
#z$width_manual <- z$upper_manual - z$lower_manual*sqrt(0.632)
#View(z)

# Check row count after ommitting NA
nrow(rep_conf)
```

```
## [1] 61
```

```r
# Confidence Interval for Full Model ------------------------------------------
# Calculate confidence interval and rename the columns
full_model_conf <- data.frame(confint(full_model, level=0.975)) %>%
                   #na.omit() %>%
                   dplyr::rename(lower_full = 1, upper_full = 2)

# Calculate Width
full_model_conf <- full_model_conf %>%
                   #mutate(index=1:nrow(full_model_conf)) %>%
                   #filter(index %in% (2:48)) %>%
                   mutate(width_full=upper_full-lower_full)

# Check row count
nrow(full_model_conf)
```

```
## [1] 61
```

```r
#t <- cbind(rep_conf, full_model_conf)

row.names(rep_conf) == row.names(full_model_conf)
```

```
##  [1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [16] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [31] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [46] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [61] TRUE
```

```r
#View(cbind(row.names(rep_conf), row.names(full_model_conf)))
```

Determine how many of the repeated sample CI's are tighter

```r
# Combine the 2 dataframes and remove NA values
calc <- cbind(rep_conf, full_model_conf) %>% na.omit()

#Calculate how many of the repeated sample CI's are tighter or broader than the full model CI's. If the
```

```r
# 1 means the CI is tighter (width of repeated is smaller)
calc$tighter_CI_flag <- ifelse(calc$width < calc$width_full, 1, 0)

print(calc)
```

```
##                                         lower        upper       width
## (Intercept)                          6434.512462  6594.377548 127.0902300
## Duration                              126.658061   127.326724   0.5315769
## InstallmentRatePercentage            -785.728963  -779.812879   4.7031936
## ResidenceDuration                     -56.720384   -50.794353   4.7111008
## Age                                     5.300337     6.024657   0.5758232
## NumberExistingCredits                  69.363798    81.822830   9.9047346
## NumberPeopleMaintenance              -216.003986  -199.915043  12.7904564
## Telephone                            -485.081845  -471.300634  10.9558456
## ForeignWorker                        -252.202656  -221.248928  24.6077270
## CheckingAccountStatus.lt.0           -111.010789   -95.571992  12.2736005
## CheckingAccountStatus.0.to.200        198.371108   213.419289  11.9630674
## CheckingAccountStatus.gt.200         -625.443188  -607.846584  13.9890232
## CreditHistory.NoCredit.AllPaid        828.778975   870.217831  32.9432387
## CreditHistory.ThisBank.AllPaid        -63.992056   -31.989438  25.4415777
## CreditHistory.PaidDuly                -23.562737    -7.771061  12.5541347
## CreditHistory.Delay                   101.276790   126.647376  20.1692174
## Purpose.NewCar                      -1838.362958 -1697.864249 111.6942644
## Purpose.UsedCar                     -1201.222149 -1061.166146 111.3423206
## Purpose.Furniture.Equipment         -1921.369565 -1781.601264 111.1136015
## Purpose.Radio.Television            -2155.367272 -2016.101729 110.7139173
## Purpose.DomesticAppliance           -2554.168943 -2409.308773 115.1615578
## Purpose.Repairs                     -1782.423125 -1638.721719 114.2403585
## Purpose.Education                   -1977.357123 -1836.845805 111.7042881
## Purpose.Business                    -2063.524192 -1921.755079 112.7042160
## SavingsAccountBonds.lt.100           -338.218770  -320.660118  13.9588517
## SavingsAccountBonds.100.to.500       -575.839300  -553.880984  17.4565155
## SavingsAccountBonds.500.to.1000      -671.130904  -647.259223  18.9776114
## SavingsAccountBonds.gt.1000          -398.022327  -374.894888  18.3859508
## EmploymentDuration.lt.1                94.460578   134.057506  31.4789355
## EmploymentDuration.1.to.4              28.761788    68.201164  31.3536839
## EmploymentDuration.4.to.7              89.356428   129.842341  32.1856648
## EmploymentDuration.gt.7              -178.787313  -139.836985  30.9648983
## Personal.Male.Divorced.Seperated      465.074755   495.948528  24.5441640
## Personal.Female.NotSingle             270.520761   286.663095  12.8329019
## Personal.Male.Single                  726.710725   743.725863  13.5267668
## OtherDebtorsGuarantors.None           119.128733   139.917054  16.5263880
## OtherDebtorsGuarantors.CoApplicant    718.892800   753.953217  27.8724802
## Property.RealEstate                  -856.026216  -819.561845  28.9886012
## Property.Insurance                   -609.422988  -571.984806  29.7627661
## Property.CarOther                    -584.197187  -548.042673  28.7422704
## OtherInstallmentPlans.Bank           -159.867481  -141.688095  14.4523259
## OtherInstallmentPlans.Stores          -61.317380   -28.667433  25.9561950
## Housing.Rent                          204.495789   249.638895  35.8880592
## Housing.Own                            86.272147   130.884024  35.4657403
## Job.UnemployedUnskilled             -1726.546330 -1650.536866  60.4263287
## Job.UnskilledResident               -1206.527835 -1178.528589  22.2589603
## Job.SkilledEmployee                 -1259.527770 -1234.348310  20.0172750
```

```
##                                    lower_full upper_full width_full
## (Intercept)                        4435.763177 8510.72827 4074.96509
## Duration                            115.088661  139.36742   24.27876
## InstallmentRatePercentage          -905.853655 -660.29769  245.55597
## ResidenceDuration                  -187.110949   82.96651  270.07746
## Age                                  -7.949048   19.45313   27.40218
## NumberExistingCredits              -210.442810  361.15444  571.59725
## NumberPeopleMaintenance            -586.216316  189.65159  775.86791
## Telephone                          -783.779788 -182.95809  600.82169
## ForeignWorker                      -969.408524  469.46575 1438.87427
## CheckingAccountStatus.lt.0         -456.029588  247.86854  703.89813
## CheckingAccountStatus.0.to.200     -130.084971  556.99291  687.07788
## CheckingAccountStatus.gt.200      -1181.974742  -47.59962 1134.37512
## CreditHistory.NoCredit.AllPaid      128.439679 1587.91850 1459.47882
## CreditHistory.ThisBank.AllPaid     -758.499916  657.85144 1416.35136
## CreditHistory.PaidDuly             -388.464343  356.75993  745.22427
## CreditHistory.Delay                -418.879276  624.44849 1043.32777
## Purpose.NewCar                    -3030.628284 -483.49542 2547.13286
## Purpose.UsedCar                   -2421.080908  182.47975 2603.56066
## Purpose.Furniture.Equipment       -3125.960277 -546.22404 2579.73624
## Purpose.Radio.Television          -3353.554841 -789.64918 2563.90566
## Purpose.DomesticAppliance         -4208.801155 -719.32644 3489.47471
## Purpose.Repairs                   -3243.361373 -172.20128 3071.16010
## Purpose.Education                 -3276.919675 -507.65935 2769.26033
## Purpose.Business                  -3298.700610 -680.23160 2618.46901
## SavingsAccountBonds.lt.100         -690.470380   36.45710  726.92748
## SavingsAccountBonds.100.to.500    -1086.074853  -52.39488 1033.67997
## SavingsAccountBonds.500.to.1000   -1248.009333  -39.04777 1208.96157
## SavingsAccountBonds.gt.1000       -1060.128734  288.15576 1348.28449
## EmploymentDuration.lt.1            -593.037232  823.74177 1416.77900
## EmploymentDuration.1.to.4          -625.352368  729.00297 1354.35534
## EmploymentDuration.4.to.7          -594.565719  821.28101 1415.84672
## EmploymentDuration.gt.7            -838.354958  511.97675 1350.33171
## Personal.Male.Divorced.Seperated   -265.422973 1226.09653 1491.51950
## Personal.Female.NotSingle          -217.311733  781.50137  998.81310
## Personal.Male.Single                236.117378 1224.21708  988.09970
## OtherDebtorsGuarantors.None        -479.385889  756.81195 1236.19784
## OtherDebtorsGuarantors.CoApplicant -129.824867 1634.19095 1764.01582
## Property.RealEstate               -1486.050998 -195.94527 1290.10573
## Property.Insurance                -1225.443886   47.84172 1273.28560
## Property.CarOther                 -1189.674581   48.16984 1237.84442
## OtherInstallmentPlans.Bank         -541.897489  254.08320  795.98069
## OtherInstallmentPlans.Stores       -698.593286  572.81307 1271.40635
## Housing.Rent                       -492.356833  979.71700 1472.07383
## Housing.Own                        -571.142512  834.00691 1405.14942
## Job.UnemployedUnskilled           -2751.756722 -678.46603 2073.29069
## Job.UnskilledResident             -1741.394635 -656.02527 1085.36936
## Job.SkilledEmployee               -1693.146450 -814.65400  878.49245
##                                   tighter_CI_flag
## (Intercept)                                     1
## Duration                                        1
## InstallmentRatePercentage                       1
## ResidenceDuration                               1
## Age                                             1
```

```
## NumberExistingCredits                          1
## NumberPeopleMaintenance                        1
## Telephone                                      1
## ForeignWorker                                  1
## CheckingAccountStatus.lt.0                     1
## CheckingAccountStatus.0.to.200                 1
## CheckingAccountStatus.gt.200                   1
## CreditHistory.NoCredit.AllPaid                 1
## CreditHistory.ThisBank.AllPaid                 1
## CreditHistory.PaidDuly                         1
## CreditHistory.Delay                            1
## Purpose.NewCar                                 1
## Purpose.UsedCar                                1
## Purpose.Furniture.Equipment                    1
## Purpose.Radio.Television                       1
## Purpose.DomesticAppliance                      1
## Purpose.Repairs                                1
## Purpose.Education                              1
## Purpose.Business                               1
## SavingsAccountBonds.lt.100                     1
## SavingsAccountBonds.100.to.500                 1
## SavingsAccountBonds.500.to.1000                1
## SavingsAccountBonds.gt.1000                    1
## EmploymentDuration.lt.1                        1
## EmploymentDuration.1.to.4                      1
## EmploymentDuration.4.to.7                      1
## EmploymentDuration.gt.7                        1
## Personal.Male.Divorced.Seperated               1
## Personal.Female.NotSingle                      1
## Personal.Male.Single                           1
## OtherDebtorsGuarantors.None                    1
## OtherDebtorsGuarantors.CoApplicant             1
## Property.RealEstate                            1
## Property.Insurance                             1
## Property.CarOther                              1
## OtherInstallmentPlans.Bank                     1
## OtherInstallmentPlans.Stores                   1
## Housing.Rent                                   1
## Housing.Own                                    1
## Job.UnemployedUnskilled                        1
## Job.UnskilledResident                          1
## Job.SkilledEmployee                            1
```

```
percent <- sum(calc$tighter_CI_flag)/nrow(calc)
print(percent*100)
```

```
## [1] 100
```

```
sum(calc$tighter_CI_flag)
```

```
## [1] 47
```

Conclusion: 100% of the simulated/repeated model's CI's are tighter/smaller. In other words, of the 47 columns left after removing NA's and the class column, 47 of the columns' confidence intervals from the repeated samples are smaller/tighter than those comapred to the CI's from the full model.

This tells us that when we repeat the model 1,000 times, the confidence in the best coefficients for each independent variable has increased (the range of our confidence intervals are smaller). Intuitively this makes sense because instead of just running 1 model and trying to fit the best coefficients, we have now done this 1,000 times and taken averages to make this determination. If we were to sample 10,000 times, the confidence intervals would be even tighter. There should be convergence at some point (diminishing returns), but there will be an improvement event passed 1,000.

In many instances, the repeated model's coefficient means were quite different from the single model we saved the coefficients for. The median difference between the repeated model mean and the corresponding saved model coefficients was 21.5%. This tells us that running just 1 model does not accurately capture what we can assume would be a "better" coefficient to use – models should be run multiples time to find the optimal fit.