R setup

```
library(readr)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(fitdistrplus)
```

```
## Loading required package: MASS
```

```
##
## Attaching package: 'MASS'
```

```
## The following object is masked from 'package:dplyr':
##
##     select
```

```
## Loading required package: survival
```

```
library(ggplot2)
library(olsrr)
```

```
##
## Attaching package: 'olsrr'
```

```
## The following object is masked from 'package:MASS':
##
##     cement
```

```
## The following object is masked from 'package:datasets':
##
##     rivers
```

```r
library(rpart)
library(rpart.plot)
library(caret)
```

```
## Loading required package: lattice
```

```
##
## Attaching package: 'caret'
```

```
## The following object is masked from 'package:survival':
##
##     cluster
```

```r
library(randomForest)
```

```
## randomForest 4.7-1.2
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```
##
## Attaching package: 'randomForest'
```

```
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
## The following object is masked from 'package:dplyr':
##
##     combine
```

```r
library(glue)
```

Problem 4

Setup

```
set.seed(15072)

df_ames <- read_csv("/Users/riyaparikh_computeracct/Downloads/MIT/15.072_AdvancedAnalyti
csEdge/deliverable2-analyticsedge-mit/ames.csv", show_col_types = FALSE)

# training (70%) and test (30%) partition
nrow = nrow(df_ames)
train_index <- sample(1:nrow, size = 0.7* nrow)
train_ames <- df_ames[train_index, ]
test_ames <- df_ames[-train_index, ]
```

Part a

```
set.seed(15072)
mod_linear_intial <- lm(SalePrice ~ ., data = train_ames)
summary(mod_linear_intial)
```

```
##
## Call:
## lm(formula = SalePrice ~ ., data = train_ames)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -304836  -10699     -42   10472  129099
##
## Coefficients: (7 not defined because of singularities)
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -3.177e+05  8.923e+05  -0.356 0.721876
## MSZoningRL               4.069e+03  3.950e+03   1.030 0.303126
## MSZoningRM               4.903e+03  4.666e+03   1.051 0.293482
## LotFrontage             -1.302e+02  4.290e+01  -3.035 0.002437 **
## LotArea                  1.527e-01  1.702e-01   0.897 0.369689
## StreetPave              -9.429e+02  1.511e+04  -0.062 0.950249
## AlleyNo Alley            4.545e+03  3.329e+03   1.365 0.172329
## AlleyPave                2.907e+03  5.056e+03   0.575 0.565398
## LotShapeMod+ IR         -1.345e+03  3.536e+03  -0.380 0.703705
## LotShapeReg             -6.858e+02  1.367e+03  -0.502 0.616051
## LandContourHLS           1.889e+04  4.199e+03   4.498 7.31e-06 ***
## LandContourLow           4.018e+03  5.384e+03   0.746 0.455535
## LandContourLvl           1.167e+04  3.084e+03   3.782 0.000161 ***
## LotConfigCulDSac         6.310e+02  3.035e+03   0.208 0.835326
## LotConfigFR2            -5.913e+03  3.624e+03  -1.632 0.102931
## LotConfigFR3            -4.961e+02  7.475e+03  -0.066 0.947086
## LotConfigInside         -1.746e+03  1.552e+03  -1.125 0.260796
## LandSlopeNot Gtl         9.969e+03  3.339e+03   2.986 0.002866 **
## NeighborhoodBlueste     -7.305e+03  1.301e+04  -0.561 0.574572
## NeighborhoodBrDale       9.959e+03  9.714e+03   1.025 0.305392
## NeighborhoodBrkSide     -6.574e+03  8.148e+03  -0.807 0.419900
## NeighborhoodClearCr      7.643e+03  8.260e+03   0.925 0.354913
## NeighborhoodCollgCr      2.730e+03  6.628e+03   0.412 0.680465
## NeighborhoodCrawfor      2.022e+04  7.442e+03   2.717 0.006654 **
## NeighborhoodEdwards     -1.947e+04  7.089e+03  -2.746 0.006086 **
## NeighborhoodGilbert     -6.953e+03  6.904e+03  -1.007 0.313999
## NeighborhoodGreens       1.098e+04  1.394e+04   0.788 0.430975
## NeighborhoodIDOTRR      -1.297e+04  8.623e+03  -1.504 0.132676
## NeighborhoodMeadowV     -1.733e+04  8.862e+03  -1.955 0.050728 .
## NeighborhoodMitchel     -7.251e+03  7.151e+03  -1.014 0.310751
## NeighborhoodNAmes       -8.649e+03  7.014e+03  -1.233 0.217709
## NeighborhoodNoRidge      3.915e+04  7.527e+03   5.201 2.21e-07 ***
## NeighborhoodNPkVill      1.368e+04  9.349e+03   1.464 0.143501
## NeighborhoodNridgHt      4.249e+04  6.880e+03   6.175 8.15e-10 ***
## NeighborhoodNWAmes      -4.111e+03  7.192e+03  -0.572 0.567597
## NeighborhoodOldTown     -1.447e+04  8.170e+03  -1.771 0.076773 .
## NeighborhoodSawyer      -8.414e+03  7.225e+03  -1.165 0.244366
## NeighborhoodSawyerW     -1.783e+03  6.879e+03  -0.259 0.795571
## NeighborhoodSomerst      2.453e+04  7.379e+03   3.325 0.000903 ***
## NeighborhoodStoneBr      4.084e+04  7.629e+03   5.353 9.79e-08 ***
## NeighborhoodSWISU       -1.278e+04  8.391e+03  -1.523 0.127936
## NeighborhoodTimber       1.118e+04  7.199e+03   1.553 0.120521
```

```
## NeighborhoodVeenker      3.282e+04  9.467e+03   3.467 0.000539 ***
## Condition1Feedr          2.851e+03  4.172e+03   0.683 0.494457
## Condition1Norm           1.107e+04  3.486e+03   3.176 0.001521 **
## Condition1PosA           2.523e+04  7.255e+03   3.478 0.000518 ***
## Condition1PosN           1.302e+04  5.864e+03   2.221 0.026490 *
## Condition1RRAe          -7.330e+02  6.691e+03  -0.110 0.912777
## Condition1RRAn           3.548e+03  5.709e+03   0.621 0.534376
## Condition1RRNe          -3.459e+03  1.142e+04  -0.303 0.762068
## Condition1RRNn           7.658e+03  1.165e+04   0.657 0.510981
## Condition2Other         -9.149e+03  5.933e+03  -1.542 0.123246
## BldgType2fmCon          -4.286e+03  4.744e+03  -0.904 0.366333
## BldgTypeDuplex          -9.778e+03  5.290e+03  -1.848 0.064702 .
## BldgTypeTwnhs           -3.281e+04  4.805e+03  -6.829 1.17e-11 ***
## BldgTypeTwnhsE          -2.633e+04  3.242e+03  -8.120 8.56e-16 ***
## HouseStyle1.5Unf         2.420e+03  7.672e+03   0.315 0.752518
## HouseStyle1Story         2.689e+02  3.201e+03   0.084 0.933060
## HouseStyle2.5Fin        -6.680e+03  1.322e+04  -0.505 0.613509
## HouseStyle2.5Unf        -8.216e+02  7.093e+03  -0.116 0.907809
## HouseStyle2Story        -2.559e+02  2.709e+03  -0.094 0.924765
## HouseStyleSFoyer        -7.635e+02  4.698e+03  -0.163 0.870919
## HouseStyleSLvl          -3.142e+03  4.035e+03  -0.779 0.436318
## YearBuilt                1.014e+02  6.223e+01   1.630 0.103226
## YearRemodAdd             2.293e+02  4.299e+01   5.335 1.08e-07 ***
## RoofStyleGable           6.241e+03  1.026e+04   0.608 0.542992
## RoofStyleGambrel         5.263e+03  1.210e+04   0.435 0.663666
## RoofStyleHip             9.114e+03  1.029e+04   0.885 0.376122
## RoofStyleMansard         1.070e+04  1.463e+04   0.731 0.464798
## RoofStyleShed            2.681e+04  1.498e+04   1.790 0.073599 .
## RoofMatlOther            2.234e+03  6.935e+03   0.322 0.747375
## Exterior1stMetalSd      -3.430e+03  7.028e+03  -0.488 0.625576
## Exterior1stOther         7.347e+03  3.580e+03   2.052 0.040284 *
## Exterior1stVinylSd      -1.209e+04  7.327e+03  -1.650 0.099182 .
## Exterior1stWd Sdng      -2.111e+03  4.512e+03  -0.468 0.639957
## Exterior2ndMetalSd       8.355e+03  7.041e+03   1.187 0.235517
## Exterior2ndOther        -3.036e+03  3.545e+03  -0.856 0.391840
## Exterior2ndVinylSd       1.525e+04  7.359e+03   2.072 0.038427 *
## Exterior2ndWd Sdng       6.332e+03  4.589e+03   1.380 0.167758
## MasVnrTypeBrkFace        5.037e+03  6.667e+03   0.755 0.450049
## MasVnrTypeNone           5.767e+03  6.673e+03   0.864 0.387601
## MasVnrTypeStone          3.461e+03  6.933e+03   0.499 0.617665
## MasVnrArea               4.298e+00  5.231e+00   0.822 0.411420
## ExterQualFa             -1.902e+04  8.283e+03  -2.296 0.021803 *
## ExterQualGd             -1.110e+04  4.087e+03  -2.715 0.006681 **
## ExterQualTA             -2.006e+04  4.527e+03  -4.430 9.98e-06 ***
## ExterCondFa             -1.396e+04  1.118e+04  -1.248 0.212233
## ExterCondGd             -4.832e+03  1.011e+04  -0.478 0.632622
## ExterCondTA             -4.194e+03  1.006e+04  -0.417 0.676711
## FoundationCBlock         4.958e+03  2.542e+03   1.950 0.051307 .
## FoundationPConc          5.283e+03  2.828e+03   1.868 0.061925 .
## FoundationSlab           6.251e+03  7.628e+03   0.819 0.412638
## FoundationStone          3.633e+03  9.178e+03   0.396 0.692304
## FoundationWood           7.703e+02  1.254e+04   0.061 0.951014
```

```
## BsmtQualFa             -1.975e+04  4.962e+03  -3.981 7.14e-05 ***
## BsmtQualGd             -1.771e+04  2.817e+03  -6.286 4.07e-10 ***
## BsmtQualNo Basement    -2.763e+04  9.904e+03  -2.790 0.005326 **
## BsmtQualTA             -1.560e+04  3.503e+03  -4.454 8.93e-06 ***
## BsmtCondGd              3.513e+03  4.220e+03   0.832 0.405304
## BsmtCondNo Basement            NA         NA      NA       NA
## BsmtCondPo             -3.550e+02  1.783e+04  -0.020 0.984114
## BsmtCondTA              1.987e+03  3.266e+03   0.608 0.542935
## BsmtExposureGd          1.072e+04  2.555e+03   4.193 2.89e-05 ***
## BsmtExposureMn         -6.323e+03  2.564e+03  -2.466 0.013746 *
## BsmtExposureNo Basement        NA         NA      NA       NA
## BsmtExposureNo Exposure -4.749e+03  1.907e+03  -2.490 0.012858 *
## BsmtFinType1BLQ        -6.945e+02  2.341e+03  -0.297 0.766775
## BsmtFinType1GLQ         5.324e+03  2.119e+03   2.512 0.012088 *
## BsmtFinType1LwQ        -6.536e+03  2.935e+03  -2.227 0.026072 *
## BsmtFinType1No Basement        NA         NA      NA       NA
## BsmtFinType1Rec        -3.041e+03  2.407e+03  -1.263 0.206743
## BsmtFinType1Unf        -3.161e+03  2.423e+03  -1.304 0.192289
## BsmtFinSF1              1.083e+01  3.943e+00   2.748 0.006057 **
## BsmtFinType2BLQ        -2.744e+03  5.329e+03  -0.515 0.606691
## BsmtFinType2GLQ         3.599e+03  6.266e+03   0.574 0.565824
## BsmtFinType2LwQ        -4.531e+03  5.176e+03  -0.875 0.381506
## BsmtFinType2No Basement        NA         NA      NA       NA
## BsmtFinType2Rec        -2.265e+03  4.986e+03  -0.454 0.649663
## BsmtFinType2Unf         7.536e+02  5.028e+03   0.150 0.880878
## BsmtFinSF2              1.401e+01  6.868e+00   2.039 0.041547 *
## BsmtUnfSF               8.281e+00  3.673e+00   2.255 0.024268 *
## TotalBsmtSF                    NA         NA      NA       NA
## HeatingHotW             3.684e+03  6.128e+03   0.601 0.547788
## HeatingOther           -5.718e+02  9.070e+03  -0.063 0.949734
## HeatingQCFa            -7.305e+03  3.544e+03  -2.061 0.039442 *
## HeatingQCGd            -1.609e+03  1.704e+03  -0.944 0.345282
## HeatingQCTA            -4.376e+03  1.683e+03  -2.599 0.009413 **
## CentralAirY             1.661e+03  3.011e+03   0.552 0.581256
## ElectricalFF           -3.990e+01  4.859e+03  -0.008 0.993449
## ElectricalFP            7.554e+03  1.145e+04   0.660 0.509590
## ElectricalSB            3.966e+01  2.449e+03   0.016 0.987081
## X1stFlrSF               4.387e+01  4.207e+00  10.429  < 2e-16 ***
## X2ndFlrSF               4.113e+01  4.771e+00   8.621  < 2e-16 ***
## LowQualFinSF            2.020e+01  1.331e+01   1.517 0.129328
## GrLivArea                      NA         NA      NA       NA
## BsmtFullBath            6.939e+03  1.581e+03   4.389 1.21e-05 ***
## BsmtHalfBath           -1.128e+03  2.367e+03  -0.476 0.633849
## FullBath                4.710e+03  1.821e+03   2.586 0.009783 **
## HalfBath               -7.456e+02  1.693e+03  -0.440 0.659707
## BedroomAbvGr            4.360e+02  1.103e+03   0.395 0.692567
## KitchenAbvGr           -1.196e+04  4.621e+03  -2.589 0.009693 **
## KitchenQualFa          -2.634e+04  5.315e+03  -4.955 7.92e-07 ***
## KitchenQualGd          -2.299e+04  3.207e+03  -7.170 1.09e-12 ***
## KitchenQualTA          -2.741e+04  3.550e+03  -7.721 1.91e-14 ***
## TotRmsAbvGrd           -2.736e+02  7.780e+02  -0.352 0.725121
## FunctionalMaj2         -2.363e+04  1.270e+04  -1.861 0.062964 .
```

```
## FunctionalMin1          4.314e+03  8.237e+03   0.524 0.600515    
## FunctionalMin2          2.858e+02  8.181e+03   0.035 0.972138    
## FunctionalMod          -3.856e+02  8.921e+03  -0.043 0.965529    
## FunctionalTyp           1.336e+04  7.400e+03   1.805 0.071181 .  
## Fireplaces              8.233e+03  2.242e+03   3.673 0.000247 ***
## FireplaceQuFa          -2.211e+04  5.698e+03  -3.881 0.000108 ***
## FireplaceQuGd          -1.648e+04  4.547e+03  -3.624 0.000298 ***
## FireplaceQuNo Fireplace -1.560e+04  5.286e+03  -2.952 0.003195 ** 
## FireplaceQuPo          -1.267e+04  6.688e+03  -1.894 0.058365 .  
## FireplaceQuTA          -1.763e+04  4.659e+03  -3.784 0.000159 ***
## GarageTypeA             1.774e+04  6.539e+03   2.713 0.006728 ** 
## GarageTypeBI            1.719e+04  7.156e+03   2.402 0.016395 *  
## GarageTypeBM            1.422e+04  8.279e+03   1.718 0.086021 .  
## GarageTypeCP            5.891e+03  9.526e+03   0.618 0.536416    
## GarageTypeD             1.255e+04  6.554e+03   1.915 0.055707 .  
## GarageTypeNone         -2.353e+05  9.418e+04  -2.499 0.012557 *  
## GarageYrBlt            -1.305e+02  4.873e+01  -2.679 0.007449 ** 
## GarageFinishNone               NA         NA      NA       NA    
## GarageFinishRFn        -7.442e+03  1.691e+03  -4.401 1.14e-05 ***
## GarageFinishUnf        -5.400e+03  2.007e+03  -2.691 0.007192 ** 
## GarageCars              9.267e+03  1.911e+03   4.850 1.34e-06 ***
## GarageArea              1.634e+01  6.968e+00   2.344 0.019169 *  
## GarageQualTA            3.165e+03  2.824e+03   1.121 0.262591    
## PavedDriveP            -1.757e+03  4.410e+03  -0.398 0.690339    
## PavedDriveY             1.357e+03  2.834e+03   0.479 0.632227    
## WoodDeckSF              1.186e+01  5.013e+00   2.366 0.018095 *  
## OpenPorchSF            -8.345e+00  9.283e+00  -0.899 0.368790    
## EnclosedPorch           1.303e+01  1.028e+01   1.268 0.205029    
## X3SsnPorch              3.304e+01  2.217e+01   1.490 0.136281    
## ScreenPorch             3.349e+01  1.008e+01   3.322 0.000910 ***
## PoolArea                1.516e+03  1.493e+02  10.153  < 2e-16 ***
## PoolQCNo Pool           9.924e+05  9.212e+04  10.773  < 2e-16 ***
## PoolQCTA                1.287e+05  3.064e+04   4.200 2.80e-05 ***
## FenceGdWo              -1.410e+03  4.091e+03  -0.345 0.730437    
## FenceMnPrv             -3.792e+03  3.213e+03  -1.180 0.238039    
## FenceMnWw              -3.097e+03  9.594e+03  -0.323 0.746854    
## FenceNo Fence          -3.780e+03  2.890e+03  -1.308 0.190940    
## MiscFeatureNo Feature   1.257e+03  3.037e+03   0.414 0.679002    
## MoSold                 -4.768e+01  2.062e+02  -0.231 0.817148    
## YrSold                 -4.858e+02  4.362e+02  -1.114 0.265620    
## SaleTypeOther          -7.106e+03  3.553e+03  -2.000 0.045670 *  
## SaleTypeWarranty Deed  -6.050e+03  2.470e+03  -2.449 0.014414 *  
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 23040 on 1791 degrees of freedom
## Multiple R-squared:  0.901,  Adjusted R-squared:  0.8911 
## F-statistic: 90.57 on 180 and 1791 DF,  p-value: < 2.2e-16
```

```
mod_linear_olsrr <- ols_step_backward_p(mod_linear_intial, p_val = 0.05, progress = TRU
E)
```

```
## Backward Elimination Method
## ---------------------------
##
## Candidate Terms:
##
## 1. MSZoning
## 2. LotFrontage
## 3. LotArea
## 4. Street
## 5. Alley
## 6. LotShape
## 7. LandContour
## 8. LotConfig
## 9. LandSlope
## 10. Neighborhood
## 11. Condition1
## 12. Condition2
## 13. BldgType
## 14. HouseStyle
## 15. YearBuilt
## 16. YearRemodAdd
## 17. RoofStyle
## 18. RoofMatl
## 19. Exterior1st
## 20. Exterior2nd
## 21. MasVnrType
## 22. MasVnrArea
## 23. ExterQual
## 24. ExterCond
## 25. Foundation
## 26. BsmtQual
## 27. BsmtCond
## 28. BsmtExposure
## 29. BsmtFinType1
## 30. BsmtFinSF1
## 31. BsmtFinType2
## 32. BsmtFinSF2
## 33. BsmtUnfSF
## 34. TotalBsmtSF
## 35. Heating
## 36. HeatingQC
## 37. CentralAir
## 38. Electrical
## 39. X1stFlrSF
## 40. X2ndFlrSF
## 41. LowQualFinSF
## 42. GrLivArea
## 43. BsmtFullBath
## 44. BsmtHalfBath
## 45. FullBath
## 46. HalfBath
## 47. BedroomAbvGr
```

```
## 48. KitchenAbvGr
## 49. KitchenQual
## 50. TotRmsAbvGrd
## 51. Functional
## 52. Fireplaces
## 53. FireplaceQu
## 54. GarageType
## 55. GarageYrBlt
## 56. GarageFinish
## 57. GarageCars
## 58. GarageArea
## 59. GarageQual
## 60. PavedDrive
## 61. WoodDeckSF
## 62. OpenPorchSF
## 63. EnclosedPorch
## 64. X3SsnPorch
## 65. ScreenPorch
## 66. PoolArea
## 67. PoolQC
## 68. Fence
## 69. MiscFeature
## 70. MoSold
## 71. YrSold
## 72. SaleType
##
##
## Variables Removed:
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => Street
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => MoSold
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => RoofMatl
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => TotRmsAbvGrd
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => BedroomAbvGr
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => Electrical
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => Heating
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => MiscFeature
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => HalfBath
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => CentralAir
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => LotShape
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => HouseStyle
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => BsmtCond
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => BsmtHalfBath
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => MasVnrType
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => MasVnrArea
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => Fence
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => PavedDrive
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => MSZoning
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => BsmtFinType2
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => Foundation
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => Alley
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => LotArea
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => OpenPorchSF
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => LotConfig
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => YrSold
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => RoofStyle
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => Condition2
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => EnclosedPorch
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => X3SsnPorch
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => GarageQual
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
## Warning in b * sx: longer object length is not a multiple of shorter object
## length
```

```
## => ExterCond
```

```
## Note: model has aliased coefficients
##       sums of squares computed by model comparison
```

```
##
## No more variables to be removed.
```

```
summary(mod_linear_olsrr)
```

```
##          Length Class      Mode
## metrics   9     data.frame list
## model    13     lm         list
## others    1     -none-     list
```

```
mod_linear_final <- mod_linear_olsrr$model
summary(mod_linear_final)
```

```
##
## Call:
## lm(formula = paste(response, "~", paste(c(include, cterms), collapse = " + ")),
##     data = l)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -311695  -10836     -12   10820  130403
##
## Coefficients: (5 not defined because of singularities)
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -1.380e+06  1.613e+05  -8.556  < 2e-16 ***
## LotFrontage             -1.126e+02  3.877e+01  -2.904 0.003722 **
## LandContourHLS           1.915e+04  4.065e+03   4.712 2.63e-06 ***
## LandContourLow           6.996e+03  5.042e+03   1.388 0.165435
## LandContourLvl           1.233e+04  2.949e+03   4.181 3.03e-05 ***
## LandSlopeNot Gtl         1.027e+04  3.157e+03   3.252 0.001168 **
## NeighborhoodBlueste     -3.016e+03  1.223e+04  -0.247 0.805276
## NeighborhoodBrDale       1.363e+04  8.777e+03   1.553 0.120491
## NeighborhoodBrkSide     -7.414e+03  7.324e+03  -1.012 0.311506
## NeighborhoodClearCr      1.071e+04  7.804e+03   1.372 0.170333
## NeighborhoodCollgCr      3.121e+03  6.344e+03   0.492 0.622784
## NeighborhoodCrawfor      2.171e+04  7.096e+03   3.059 0.002254 **
## NeighborhoodEdwards     -1.824e+04  6.751e+03  -2.702 0.006965 **
## NeighborhoodGilbert     -6.415e+03  6.523e+03  -0.983 0.325541
## NeighborhoodGreens       1.243e+04  1.343e+04   0.926 0.354797
## NeighborhoodIDOTRR      -1.205e+04  7.549e+03  -1.597 0.110533
## NeighborhoodMeadowV     -1.432e+04  7.940e+03  -1.804 0.071419 .
## NeighborhoodMitchel     -6.924e+03  6.783e+03  -1.021 0.307530
## NeighborhoodNAmes       -6.920e+03  6.657e+03  -1.040 0.298703
## NeighborhoodNoRidge      4.115e+04  7.134e+03   5.768 9.40e-09 ***
## NeighborhoodNPkVill      1.416e+04  8.923e+03   1.587 0.112595
## NeighborhoodNridgHt      4.279e+04  6.551e+03   6.532 8.36e-11 ***
## NeighborhoodNWAmes      -2.902e+03  6.855e+03  -0.423 0.672064
## NeighborhoodOldTown     -1.385e+04  7.103e+03  -1.950 0.051347 .
## NeighborhoodSawyer      -6.016e+03  6.874e+03  -0.875 0.381581
## NeighborhoodSawyerW     -1.484e+03  6.612e+03  -0.224 0.822474
## NeighborhoodSomerst      2.036e+04  6.296e+03   3.234 0.001241 **
## NeighborhoodStoneBr      4.217e+04  7.359e+03   5.730 1.17e-08 ***
## NeighborhoodSWISU       -1.208e+04  7.936e+03  -1.522 0.128178
## NeighborhoodTimber       1.179e+04  6.912e+03   1.705 0.088300 .
## NeighborhoodVeenker      3.512e+04  9.046e+03   3.882 0.000107 ***
## Condition1Feedr          2.651e+03  4.016e+03   0.660 0.509246
## Condition1Norm           1.154e+04  3.341e+03   3.453 0.000567 ***
## Condition1PosA           2.593e+04  7.001e+03   3.703 0.000219 ***
## Condition1PosN           1.298e+04  5.640e+03   2.301 0.021512 *
## Condition1RRAe           2.077e+02  6.489e+03   0.032 0.974463
## Condition1RRAn           3.297e+03  5.473e+03   0.602 0.546950
## Condition1RRNe           1.628e+03  1.106e+04   0.147 0.882978
## Condition1RRNn           8.799e+03  1.110e+04   0.793 0.427956
## BldgType2fmCon          -5.139e+03  4.473e+03  -1.149 0.250782
## BldgTypeDuplex          -9.638e+03  4.856e+03  -1.985 0.047326 *
```

```
## BldgTypeTwnhs          -3.403e+04  4.435e+03  -7.674 2.68e-14 ***
## BldgTypeTwnhsE         -2.741e+04  2.872e+03  -9.545  < 2e-16 ***
## YearBuilt               1.588e+02  5.222e+01   3.041 0.002394 **
## YearRemodAdd            2.268e+02  4.045e+01   5.607 2.36e-08 ***
## Exterior1stMetalSd     -3.585e+03  6.875e+03  -0.522 0.602066
## Exterior1stOther        6.388e+03  3.482e+03   1.835 0.066720 .
## Exterior1stVinylSd     -1.260e+04  7.060e+03  -1.785 0.074384 .
## Exterior1stWd Sdng     -1.980e+03  4.389e+03  -0.451 0.652033
## Exterior2ndMetalSd      8.563e+03  6.872e+03   1.246 0.212913
## Exterior2ndOther       -1.972e+03  3.451e+03  -0.571 0.567786
## Exterior2ndVinylSd      1.548e+04  7.107e+03   2.178 0.029547 *
## Exterior2ndWd Sdng      6.260e+03  4.459e+03   1.404 0.160522
## ExterQualFa            -2.368e+04  7.579e+03  -3.125 0.001806 **
## ExterQualGd            -1.119e+04  3.972e+03  -2.818 0.004881 **
## ExterQualTA            -2.048e+04  4.378e+03  -4.677 3.13e-06 ***
## BsmtQualFa             -1.946e+04  4.734e+03  -4.111 4.10e-05 ***
## BsmtQualGd             -1.771e+04  2.727e+03  -6.492 1.08e-10 ***
## BsmtQualNo Basement    -2.751e+04  6.527e+03  -4.215 2.62e-05 ***
## BsmtQualTA             -1.531e+04  3.338e+03  -4.587 4.81e-06 ***
## BsmtExposureGd          1.083e+04  2.479e+03   4.367 1.33e-05 ***
## BsmtExposureMn         -5.892e+03  2.411e+03  -2.444 0.014610 *
## BsmtExposureNo Basement        NA         NA      NA       NA
## BsmtExposureNo Exposure -4.508e+03  1.709e+03  -2.637 0.008426 **
## BsmtFinType1BLQ        -2.425e+02  2.247e+03  -0.108 0.914074
## BsmtFinType1GLQ         4.403e+03  2.027e+03   2.172 0.030014 *
## BsmtFinType1LwQ        -5.687e+03  2.783e+03  -2.043 0.041146 *
## BsmtFinType1No Basement        NA         NA      NA       NA
## BsmtFinType1Rec        -2.398e+03  2.293e+03  -1.046 0.295675
## BsmtFinType1Unf        -3.488e+03  2.313e+03  -1.508 0.131748
## BsmtFinSF1              1.085e+01  3.660e+00   2.964 0.003075 **
## BsmtFinSF2              1.052e+01  4.839e+00   2.173 0.029900 *
## BsmtUnfSF               8.669e+00  3.394e+00   2.554 0.010729 *
## TotalBsmtSF                    NA         NA      NA       NA
## HeatingQCFa            -9.912e+03  3.226e+03  -3.072 0.002155 **
## HeatingQCGd            -1.881e+03  1.657e+03  -1.135 0.256552
## HeatingQCTA            -4.831e+03  1.610e+03  -3.000 0.002740 **
## X1stFlrSF               4.509e+01  3.556e+00  12.682  < 2e-16 ***
## X2ndFlrSF               4.055e+01  2.048e+00  19.801  < 2e-16 ***
## LowQualFinSF            1.584e+01  1.186e+01   1.336 0.181847
## GrLivArea                      NA         NA      NA       NA
## BsmtFullBath            7.627e+03  1.435e+03   5.316 1.19e-07 ***
## FullBath                4.151e+03  1.575e+03   2.635 0.008474 **
## KitchenAbvGr           -1.253e+04  4.232e+03  -2.961 0.003110 **
## KitchenQualFa          -2.714e+04  5.059e+03  -5.364 9.14e-08 ***
## KitchenQualGd          -2.289e+04  3.132e+03  -7.307 4.04e-13 ***
## KitchenQualTA          -2.700e+04  3.457e+03  -7.810 9.46e-15 ***
## FunctionalMaj2         -2.492e+04  1.202e+04  -2.073 0.038282 *
## FunctionalMin1          3.770e+03  7.911e+03   0.476 0.633784
## FunctionalMin2         -1.472e+03  7.770e+03  -0.189 0.849799
## FunctionalMod          -3.358e+03  8.544e+03  -0.393 0.694328
## FunctionalTyp           1.288e+04  7.080e+03   1.819 0.069083 .
## Fireplaces              8.399e+03  2.161e+03   3.886 0.000106 ***
```

```
## FireplaceQuFa          -2.154e+04  5.565e+03  -3.871 0.000112 ***
## FireplaceQuGd          -1.556e+04  4.452e+03  -3.495 0.000486 ***
## FireplaceQuNo Fireplace -1.530e+04  5.156e+03  -2.967 0.003041 **
## FireplaceQuPo          -1.282e+04  6.540e+03  -1.960 0.050145 .
## FireplaceQuTA          -1.714e+04  4.567e+03  -3.753 0.000180 ***
## GarageTypeA             1.699e+04  6.257e+03   2.716 0.006667 **
## GarageTypeBI            1.574e+04  6.750e+03   2.332 0.019794 *
## GarageTypeBM            1.193e+04  7.967e+03   1.498 0.134372
## GarageTypeCP            2.455e+03  9.143e+03   0.269 0.788321
## GarageTypeD             1.127e+04  6.275e+03   1.796 0.072728 .
## GarageTypeNone         -2.317e+05  8.915e+04  -2.599 0.009426 **
## GarageYrBlt            -1.269e+02  4.595e+01  -2.761 0.005819 **
## GarageFinishNone               NA         NA      NA       NA
## GarageFinishRFn        -7.585e+03  1.642e+03  -4.618 4.13e-06 ***
## GarageFinishUnf        -5.435e+03  1.940e+03  -2.802 0.005129 **
## GarageCars              9.235e+03  1.822e+03   5.069 4.40e-07 ***
## GarageArea              1.753e+01  6.689e+00   2.621 0.008845 **
## WoodDeckSF              1.126e+01  4.796e+00   2.347 0.019011 *
## ScreenPorch             3.098e+01  9.800e+00   3.161 0.001600 **
## PoolArea                1.504e+03  1.393e+02  10.802  < 2e-16 ***
## PoolQCNo Pool           9.862e+05  8.637e+04  11.419  < 2e-16 ***
## PoolQCTA                1.292e+05  2.935e+04   4.401 1.14e-05 ***
## SaleTypeOther          -7.814e+03  3.425e+03  -2.282 0.022625 *
## SaleTypeWarranty Deed  -5.956e+03  2.365e+03  -2.518 0.011883 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 22930 on 1860 degrees of freedom
## Multiple R-squared:  0.8983, Adjusted R-squared:  0.8922
## F-statistic: 147.9 on 111 and 1860 DF,  p-value: < 2.2e-16
```

```
# out of sample Rsqd calc
out_of_sample_predictions <- predict(mod_linear_final, newdata = test_ames)

# calculate out-of-sample R-squared
out_of_sample_r_squared <- 1 - (sum((test_ames$SalePrice - out_of_sample_predictions)^2)
/
                                sum((test_ames$SalePrice - mean(test_ames$SalePrice))^
2))
out_of_sample_r_squared
```

```
## [1] 0.825442
```

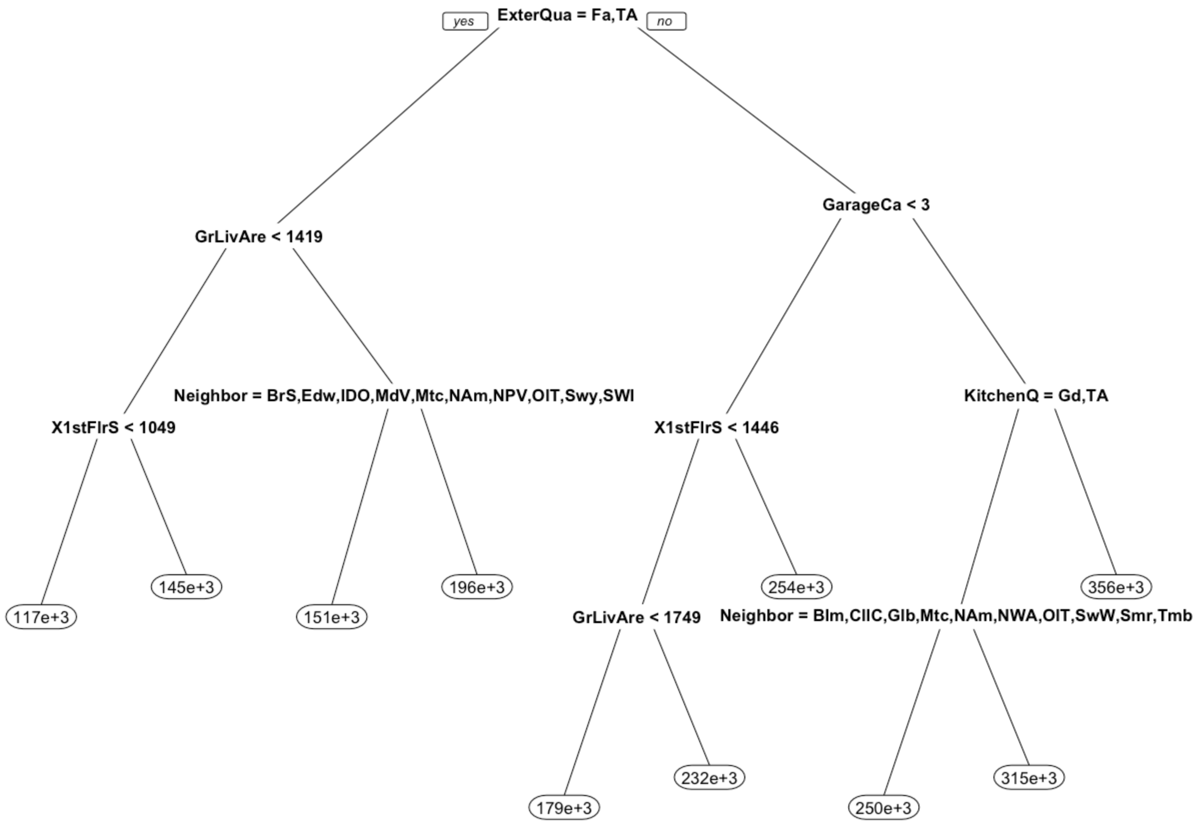
For mod_linear_final: In-sample R-squared (taken from outputted summary): 0.8983 Out-of-sample R-squared: 0.8254482

Part b

```
set.seed(15072)
library(rpart)
modelcart = rpart(data = train_ames, SalePrice ~ .)
modelcart
```

```
## n= 1972
##
## node), split, n, deviance, yval
##       * denotes terminal node
##
##  1) root 1972 9.608319e+12 178139.2
##    2) ExterQual=Fa,TA 1245 1.900199e+12 143154.8
##      4) GrLivArea< 1419 785 5.444631e+11 127737.4
##        8) X1stFlrSF< 1049 481 2.328889e+11 116714.7 *
##        9) X1stFlrSF>=1049 304 1.606640e+11 145178.0 *
##      5) GrLivArea>=1419 460 8.507225e+11 169464.9
##       10) Neighborhood=BrkSide,Edwards,IDOTRR,MeadowV,Mitchel,NAmes,NPkVill,OldTown,S
awyer,SWISU 274 3.673466e+11 151150.2 *
##       11) Neighborhood=ClearCr,CollgCr,Crawfor,Gilbert,NridgHt,NWAmes,SawyerW,Somers
t,Timber,Veenker 186 2.560787e+11 196444.6 *
##    3) ExterQual=Ex,Gd 727 3.574869e+12 238050.7
##      6) GarageCars< 2.5 510 1.269908e+12 209839.7
##       12) X1stFlrSF< 1446 373 5.675778e+11 193570.8
##         24) GrLivArea< 1748.5 269 2.177148e+11 178686.4 *
##         25) GrLivArea>=1748.5 104 1.361211e+11 232069.8 *
##       13) X1stFlrSF>=1446 137 3.348141e+11 254134.0 *
##      7) GarageCars>=2.5 217 9.451414e+11 304353.0
##       14) KitchenQual=Gd,TA 142 3.937172e+11 277137.0
##         28) Neighborhood=Blmngtn,CollgCr,Gilbert,Mitchel,NAmes,NWAmes,OldTown,Sawyer
W,Somerst,Timber 83 1.250205e+11 249986.9 *
##         29) Neighborhood=NoRidge,NridgHt,StoneBr,Veenker 59 1.214454e+11 315331.3 *
##       15) KitchenQual=Ex 75 2.471010e+11 355881.9 *
```

```
library(rpart.plot)
prp(modelcart)
```




```
# in-sample predictions
in_sample_predictions <- predict(modelcart, newdata = train_ames)

# calculate in-sample R-squared
in_sample_r_squared <- 1 - (sum((train_ames$SalePrice - in_sample_predictions)^2) /
                            sum((train_ames$SalePrice - mean(train_ames$SalePrice))^2))

# out-of-sample predictions
out_of_sample_predictions <- predict(modelcart, newdata = test_ames)

# calculate out-of-sample R-squared
out_of_sample_r_squared <- 1 - (sum((test_ames$SalePrice - out_of_sample_predictions)^2)
/
                                sum((test_ames$SalePrice - mean(test_ames$SalePrice))^
2))

cat("In-sample R²:", round(in_sample_r_squared, 4), "\n")
```

```
## In-sample R²: 0.7711
```

```
cat("Out-of-sample R²:", round(out_of_sample_r_squared, 4), "\n")
```

```
## Out-of-sample R²: 0.691
```

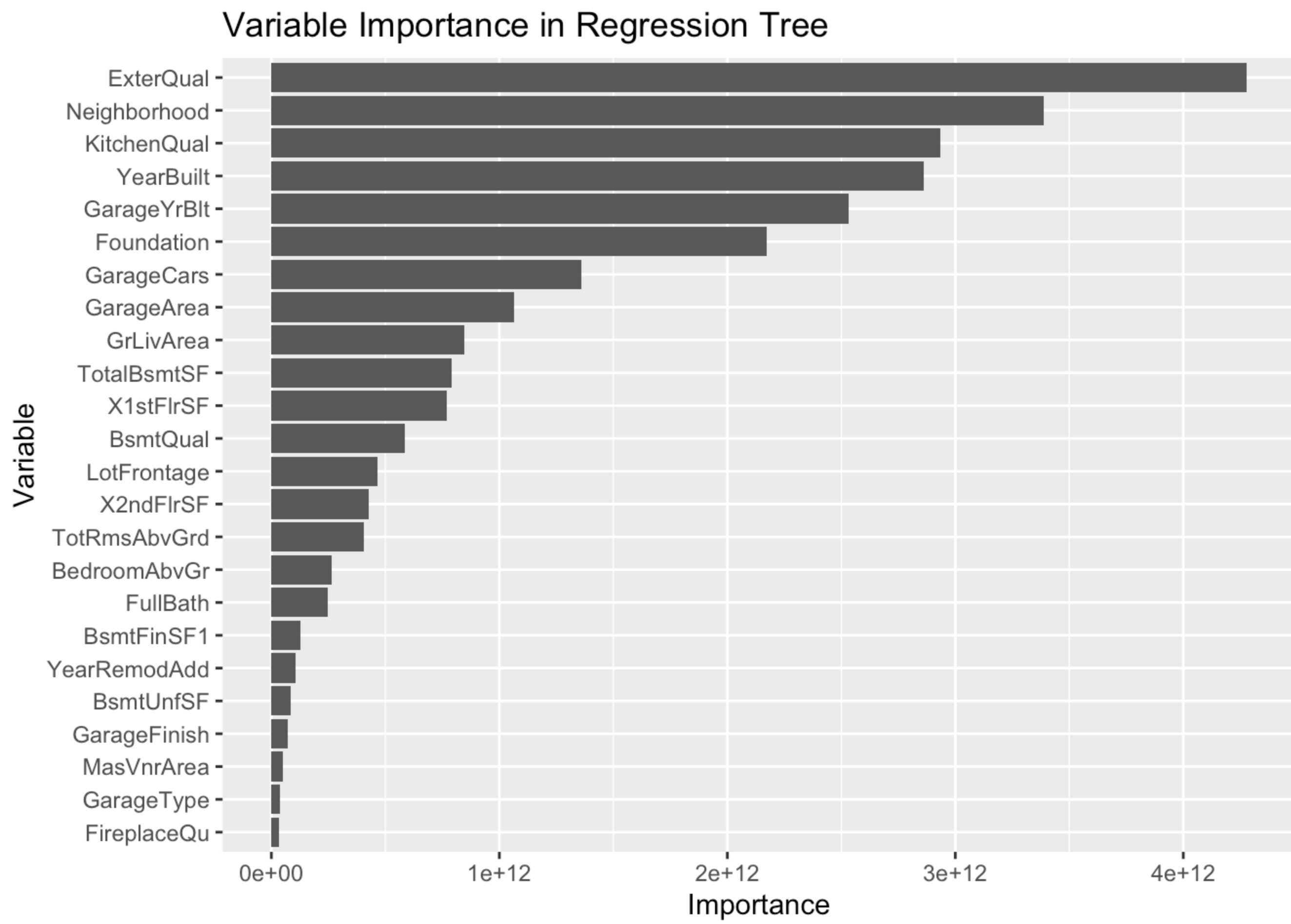
```r
set.seed(15072)
importance_scores <- modelcart$variable.importance
print(importance_scores)
```

```
##    ExterQual Neighborhood  KitchenQual    YearBuilt  GarageYrBlt   Foundation
## 4.279327e+12 3.389753e+12 2.936123e+12 2.862491e+12 2.532263e+12 2.174458e+12
##   GarageCars   GarageArea    GrLivArea  TotalBsmtSF    X1stFlrSF     BsmtQual
## 1.359819e+12 1.065296e+12 8.466353e+11 7.909058e+11 7.674546e+11 5.851225e+11
##  LotFrontage    X2ndFlrSF TotRmsAbvGrd BedroomAbvGr     FullBath   BsmtFinSF1
## 4.642459e+11 4.272400e+11 4.075687e+11 2.623970e+11 2.459194e+11 1.287648e+11
## YearRemodAdd    BsmtUnfSF GarageFinish   MasVnrArea   GarageType  FireplaceQu
## 1.048548e+11 8.584321e+10 7.209965e+10 4.991570e+10 3.772757e+10 3.493857e+10
```

```r
sorted_importance <- sort(importance_scores, decreasing = TRUE)
print(sorted_importance)
```

```
##    ExterQual Neighborhood  KitchenQual    YearBuilt  GarageYrBlt   Foundation
## 4.279327e+12 3.389753e+12 2.936123e+12 2.862491e+12 2.532263e+12 2.174458e+12
##   GarageCars   GarageArea    GrLivArea  TotalBsmtSF    X1stFlrSF     BsmtQual
## 1.359819e+12 1.065296e+12 8.466353e+11 7.909058e+11 7.674546e+11 5.851225e+11
##  LotFrontage    X2ndFlrSF TotRmsAbvGrd BedroomAbvGr     FullBath   BsmtFinSF1
## 4.642459e+11 4.272400e+11 4.075687e+11 2.623970e+11 2.459194e+11 1.287648e+11
## YearRemodAdd    BsmtUnfSF GarageFinish   MasVnrArea   GarageType  FireplaceQu
## 1.048548e+11 8.584321e+10 7.209965e+10 4.991570e+10 3.772757e+10 3.493857e+10
```

```r
library(ggplot2)
importance_df <- as.data.frame(sorted_importance)
importance_df$variable <- rownames(importance_df)
ggplot(importance_df, aes(x = reorder(variable, sorted_importance), y = sorted_importanc
e)) +
  geom_col() +
  coord_flip() +
  labs(x = "Variable", y = "Importance", title = "Variable Importance in Regression Tre
e")
```



In sample R^2 is 0.7711155 and out of sample R^2 is 0.6909755. We have included our decision tree visualization above, and we can see from this plot of feature importances that the 5 most important variables are ExterQual, Neighborhood, KitchenQual, YearBuilt, and GarageYrBlt. This makes sense because the initial splits in our tree do occur based on ExterQua, GrLivAre, and GarageCa, and Neighbor shows up as well in following splits. These features must provide the most information gain in the tree, hence they are some of the most important features that tell us more about how to predict SalePrice based on other attributes provided.

Part c

```
set.seed(15072)
coef(mod_linear_final
     )["CentralAir"]
```

```
## <NA>
##   NA
```

In order to see if it is worth it to have central air installed in order to increase the value of her home, we would want to compare the cost of installation ($15,000) to the predicted value added when a home has central air but all other factors remain constant. If the predicted value add is more than the cost, then yes it is worth it. Else, it is not going to be enough of a reason to spend the cost on the install. When we try to find the coefficient for “CentralAir” from our initial linear model, we get NA. When we try to see if “CentralAir” was one of the important features in our plot of Important Features in our decision tree, we see it doesn’t show up. Meaning, “CentralAir” is not being valued in either of our models - the noninclusion suggests 0 value add. One thing I noticed was that, during the construction of models in part a, I was getting the error of aliased coefficients. I investigated further and found that a model has “aliased coefficients” when there is linear dependency among its predictor variables, meaning one or more predictors can be perfectly expressed as a linear combination of others, resulting in redundant information and making it impossible to uniquely estimate their coefficients. It indicates potential multicollinearity issues that require addressing by removing redundant variables or using other modeling techniques. However, we were told to assume no multicollinearity, which is obviously not the case in this dataset.

Part d

```
set.seed(15072)

# defining the cp values to evaluate
cp_values <- c(5e-6, 5e-5, 5e-4, 5e-3, 5e-2)
tune_grid <- expand.grid(cp = cp_values)

# set up 10-fold cross-validation
ctrl <- trainControl(method = "cv", number = 10)

# perform cross-validation to find the best cp
set.seed(15072)
tree_model_cv <- train(
  SalePrice ~ .,
  data = train_ames,
  method = "rpart",
  trControl = ctrl,
  tuneGrid = tune_grid
)

# result of cross validation
print(tree_model_cv)
```

```
## CART
##
## 1972 samples
##   72 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 1773, 1776, 1775, 1774, 1775, 1776, ...
## Resampling results across tuning parameters:
##
##   cp     RMSE      Rsquared   MAE
##   5e-06  32402.72  0.7888318  22046.39
##   5e-05  32381.31  0.7891214  22008.86
##   5e-04  32280.79  0.7894255  21944.28
##   5e-03  35459.33  0.7410871  25650.75
##   5e-02  44703.89  0.5875329  33500.24
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was cp = 5e-04.
```

```r
set.seed(15072)

# reporting the best cp value selected by cross-validation based on lowest rmse
best_cp <- tree_model_cv$bestTune$cp
cat("The optimal cp value is:", best_cp, "\n")
```

```
## The optimal cp value is: 5e-04
```

```r
# define the final model using the best cp
final_model <- rpart(SalePrice ~ ., data = train_ames, cp = best_cp)
print(final_model)
```

```
## n= 1972
##
## node), split, n, deviance, yval
##       * denotes terminal node
##
##   1) root 1972 9.608319e+12 178139.20
##     2) ExterQual=Fa,TA 1245 1.900199e+12 143154.80
##       4) GrLivArea< 1419 785 5.444631e+11 127737.40
##         8) X1stFlrSF< 1049 481 2.328889e+11 116714.70
##          16) Neighborhood=BrDale,BrkSide,Edwards,IDOTRR,MeadowV,OldTown,SawyerW,SWISU
265 1.076367e+11 106900.90
##            32) GrLivArea< 1146 170 5.917118e+10  99635.68
##              64) TotalBsmtSF< 685 87 2.257950e+10  92467.70
##               128) GrLivArea< 952 40 5.243056e+09  84340.00 *
##               129) GrLivArea>=952 47 1.244523e+10  99384.89 *
##              65) TotalBsmtSF>=685 83 2.743616e+10 107149.10
##               130) PavedDrive=N,P 24 7.332318e+09  93667.71 *
##               131) PavedDrive=Y 59 1.396754e+10 112633.10 *
##            33) GrLivArea>=1146 95 2.343486e+10 119901.90 *
##          17) Neighborhood=Blueste,ClearCr,CollgCr,Crawfor,Gilbert,Mitchel,NAmes,NPkVi
ll,NWAmes,Sawyer,Somerst,Timber 216 6.841824e+10 128754.70
##            34) HouseStyle=1.5Unf,1Story 153 3.940272e+10 123441.70
##              68) TotalBsmtSF< 776.5 19 2.222815e+09 101400.00 *
##              69) TotalBsmtSF>=776.5 134 2.664019e+10 126567.00 *
##            35) HouseStyle=1.5Fin,2Story,SFoyer,SLvl 63 1.420769e+10 141657.80 *
##         9) X1stFlrSF>=1049 304 1.606640e+11 145178.00
##          18) Neighborhood=BrkSide,Crawfor,Edwards,IDOTRR,MeadowV,NAmes,NPkVill,OldTow
n,Sawyer,SawyerW,SWISU 236 9.176543e+10 139985.40
##            36) YearBuilt< 1953.5 41 1.257992e+10 121856.60
##              72) LotFrontage< 79.5 31 4.707429e+09 114568.40 *
##              73) LotFrontage>=79.5 10 1.121225e+09 144450.00 *
##            37) YearBuilt>=1953.5 195 6.287762e+10 143797.10
##              74) TotalBsmtSF< 472 11 3.389282e+09 112027.30 *
##              75) TotalBsmtSF>=472 184 4.772208e+10 145696.40
##               150) X1stFlrSF< 1187.5 106 2.130203e+10 140895.90 *
##               151) X1stFlrSF>=1187.5 78 2.065788e+10 152220.00 *
##          19) Neighborhood=ClearCr,CollgCr,Gilbert,Mitchel,NWAmes,Timber 68 4.045119e+
10 163199.20
##            38) BsmtExposure=Av,Mn,No Exposure 61 2.654873e+10 159246.70
##              76) GarageArea< 334.5 8 3.448840e+09 134800.00 *
##              77) GarageArea>=334.5 53 1.759708e+10 162936.80 *
##            39) BsmtExposure=Gd 7 4.644937e+09 197642.90 *
##       5) GrLivArea>=1419 460 8.507225e+11 169464.90
##        10) Neighborhood=BrkSide,Edwards,IDOTRR,MeadowV,Mitchel,NAmes,NPkVill,OldTown,
Sawyer,SWISU 274 3.673466e+11 151150.20
##          20) LotArea< 12561.5 221 1.569281e+11 143602.90
##            40) GarageQual=Other 50 2.758929e+10 120574.40 *
##            41) GarageQual=TA 171 9.507018e+10 150336.30
##              82) YearRemodAdd< 1961 59 2.011788e+10 138366.90 *
##              83) YearRemodAdd>=1961 112 6.204682e+10 156641.60
##               166) GrLivArea< 1932.5 88 3.678549e+10 151508.70
##                 332) BsmtFinSF1< 467 54 1.588062e+10 143912.30
```

```
##                    664) LotFrontage< 84 47 9.861887e+09 140184.30 *
##                    665) LotFrontage>=84 7 9.798371e+08 168942.90 *
##                  333) BsmtFinSF1>=467 34 1.283974e+10 163573.50 *
##                167) GrLivArea>=1932.5 24 1.444138e+10 175462.50
##                  334) GarageYrBlt>=1957 17 6.755721e+09 165641.20 *
##                  335) GarageYrBlt< 1957 7 2.063509e+09 199314.30 *
##           21) LotArea>=12561.5 53 1.453373e+11 182621.20
##             42) KitchenQual=Fa,TA 41 8.432780e+10 167486.00
##               84) Fireplaces< 1.5 30 3.194658e+10 148714.20
##                168) Fireplaces< 0.5 9 7.021340e+09 119766.70 *
##                169) Fireplaces>=0.5 21 1.415150e+10 161120.20
##                  338) GrLivArea< 1657 9 6.210722e+09 143444.40 *
##                  339) GrLivArea>=1657 12 3.019944e+09 174377.10 *
##               85) Fireplaces>=1.5 11 1.297864e+10 218681.80 *
##             43) KitchenQual=Ex,Gd 12 1.952767e+10 234333.30 *
##         11) Neighborhood=ClearCr,CollgCr,Crawfor,Gilbert,NridgHt,NWAmes,SawyerW,Somers
t,Timber,Veenker 186 2.560787e+11 196444.60
##           22) GrLivArea< 2093.5 155 1.341352e+11 187091.70
##             44) BsmtFinSF1< 593.5 99 5.366151e+10 176118.30
##               88) KitchenAbvGr>=1.5 8 1.897482e+09 131600.90 *
##               89) KitchenAbvGr< 1.5 91 3.451583e+10 180031.90
##                178) TotalBsmtSF< 786.5 33 1.196113e+10 170088.00
##                  356) BsmtFinSF1< 217.5 20 4.757086e+09 159856.00 *
##                  357) BsmtFinSF1>=217.5 13 1.888763e+09 185829.60 *
##                179) TotalBsmtSF>=786.5 58 1.743503e+10 185689.70 *
##             45) BsmtFinSF1>=593.5 56 4.747746e+10 206491.20
##               90) Neighborhood=Gilbert,NWAmes,SawyerW,Veenker 29 8.277487e+09 190848.8
0 *
##               91) Neighborhood=ClearCr,CollgCr,Crawfor,Somerst,Timber 27 2.448267e+10
223292.30
##                182) Exterior1st=HdBoard,VinylSd,Wd Sdng 18 6.053178e+09 208951.60 *
##                183) Exterior1st=Other 9 7.324022e+09 251973.80 *
##           23) GrLivArea>=2093.5 31 4.059107e+10 243208.80
##             46) Neighborhood=ClearCr,Crawfor,Gilbert,Timber 19 1.508205e+10 226305.30
*
##             47) Neighborhood=CollgCr,NridgHt,NWAmes,SawyerW 12 1.148445e+10 269972.80
*
##     3) ExterQual=Ex,Gd 727 3.574869e+12 238050.70
##       6) GarageCars< 2.5 510 1.269908e+12 209839.70
##        12) X1stFlrSF< 1446 373 5.675778e+11 193570.80
##          24) GrLivArea< 1748.5 269 2.177148e+11 178686.40
##            48) X1stFlrSF< 1274 194 1.194392e+11 169870.00
##              96) Neighborhood=BrkSide,ClearCr,Edwards,Mitchel,NAmes,OldTown,Sawyer,SW
ISU 38 1.386876e+10 140578.90 *
##              97) Neighborhood=Blmngtn,Blueste,CollgCr,Crawfor,Gilbert,Greens,NridgHt,
NWAmes,SawyerW,Somerst,StoneBr,Timber,Veenker 156 6.502606e+10 177005.00
##               194) GrLivArea< 1204 37 8.034938e+09 157738.70 *
##               195) GrLivArea>=1204 119 3.898687e+10 182995.30
##                 390) TotalBsmtSF< 769 49 6.439587e+09 172881.50 *
##                 391) TotalBsmtSF>=769 70 2.402650e+10 190075.00 *
##            49) X1stFlrSF>=1274 75 4.419064e+10 201491.50
##              98) Neighborhood=Blmngtn,CollgCr,Gilbert,NAmes,NWAmes,SawyerW 33 9.64521
```

```
3e+09 186641.80 *
##              99) Neighborhood=ClearCr,Greens,Mitchel,NridgHt,Somerst,StoneBr,Timber,V
eenker 42 2.155091e+10 213159.10
##               198) GarageFinish=RFn,Unf 32 6.788699e+09 204612.60 *
##               199) GarageFinish=Fin 10 4.945231e+09 240508.00 *
##          25) GrLivArea>=1748.5 104 1.361211e+11 232069.80
##            50) TotalBsmtSF< 1052.5 69 6.478386e+10 218543.70
##             100) Neighborhood=CollgCr,Edwards,Gilbert,NoRidge,NWAmes,OldTown,Sawyer,S
awyerW,SWISU,Timber 59 3.856651e+10 211397.60
##               200) BsmtQual=Fa,No Basement,TA 7 5.305994e+09 165628.60 *
##               201) BsmtQual=Gd 52 1.662296e+10 217558.80 *
##             101) Neighborhood=Crawfor,Somerst 10 5.427956e+09 260705.80 *
##            51) TotalBsmtSF>=1052.5 35 3.382601e+10 258735.60
##             102) GrLivArea< 2184 20 7.177199e+09 240141.00 *
##             103) GrLivArea>=2184 15 1.051333e+10 283528.50 *
##        13) X1stFlrSF>=1446 137 3.348141e+11 254134.00
##          26) Neighborhood=Blmngtn,CollgCr,Edwards,Mitchel,NAmes,NWAmes,OldTown,Sawyer
W,Somerst,StoneBr,Timber 99 1.529120e+11 239198.80
##            52) GrLivArea< 1592.5 47 3.941796e+10 221856.80
##             104) BsmtUnfSF>=1096.5 23 1.318671e+10 205102.20
##               208) Neighborhood=Blmngtn,CollgCr,Mitchel,NAmes,SawyerW,Timber 15 2.426
446e+09 193305.90 *
##               209) Neighborhood=Somerst 8 4.759368e+09 227220.10 *
##             105) BsmtUnfSF< 1096.5 24 1.358725e+10 237913.30
##               210) YearBuilt< 2004.5 17 3.519644e+09 227705.30 *
##               211) YearBuilt>=2004.5 7 3.993999e+09 262704.30 *
##            53) GrLivArea>=1592.5 52 8.658317e+10 254873.30
##             106) Neighborhood=CollgCr,Edwards,Mitchel,NAmes,NWAmes,OldTown,Timber 31
3.667409e+10 239100.40
##               212) BsmtExposure=Mn,No Exposure 19 1.346494e+10 226073.20 *
##               213) BsmtExposure=Av,Gd 12 1.487934e+10 259726.80 *
##             107) Neighborhood=SawyerW,Somerst,StoneBr 21 3.081187e+10 278157.10
##               214) YearRemodAdd< 1998 9 8.326120e+09 251600.00 *
##               215) YearRemodAdd>=1998 12 1.137756e+10 298075.00 *
##          27) Neighborhood=ClearCr,Crawfor,NoRidge,NridgHt,Veenker 38 1.022877e+11 293
044.00
##            54) TotalBsmtSF< 1567 13 1.464072e+10 259128.50 *
##            55) TotalBsmtSF>=1567 25 6.491780e+10 310680.00
##             110) GrLivArea< 1856.5 16 4.158005e+10 296965.00 *
##             111) GrLivArea>=1856.5 9 1.497764e+10 335062.30 *
##       7) GarageCars>=2.5 217 9.451414e+11 304353.00
##        14) KitchenQual=Gd,TA 142 3.937172e+11 277137.00
##          28) Neighborhood=Blmngtn,CollgCr,Gilbert,Mitchel,NAmes,NWAmes,OldTown,Sawyer
W,Somerst,Timber 83 1.250205e+11 249986.90
##            56) TotalBsmtSF< 1797.5 76 8.073447e+10 243560.60
##             112) GrLivArea< 2197.5 64 5.961513e+10 237688.50
##               224) BsmtFinSF1< 1145 56 4.376146e+10 232125.50
##                 448) OpenPorchSF< 22 12 5.776200e+09 208114.90 *
##                 449) OpenPorchSF>=22 44 2.918042e+10 238673.80 *
##               225) BsmtFinSF1>=1145 8 1.989257e+09 276629.80 *
##             113) GrLivArea>=2197.5 12 7.142676e+09 274878.70 *
##            57) TotalBsmtSF>=1797.5 7 7.072257e+09 319757.10 *
```

```
##         29) Neighborhood=NoRidge,NridgHt,StoneBr,Veenker 59 1.214454e+11 315331.30
##           58) TotalBsmtSF< 1743 43 5.455331e+10 301056.70
##            116) GrLivArea< 2390.5 23 1.552357e+10 282136.30
##              232) OpenPorchSF< 63 15 5.911989e+09 270826.70 *
##              233) OpenPorchSF>=63 8 4.095510e+09 303342.00 *
##            117) GrLivArea>=2390.5 20 2.132769e+10 322815.00
##              234) YearBuilt< 1995.5 9 5.237556e+09 301777.80 *
##              235) YearBuilt>=1995.5 11 8.848133e+09 340027.40 *
##           59) TotalBsmtSF>=1743 16 3.458255e+10 353694.40 *
##       15) KitchenQual=Ex 75 2.471010e+11 355881.90
##         30) BsmtUnfSF>=599 34 1.088776e+11 326350.40
##           60) Neighborhood=CollgCr,Edwards,NoRidge,Somerst 8 3.067148e+10 282116.60
*
##           61) Neighborhood=NridgHt,StoneBr,Timber 26 5.773678e+10 339960.80
##            122) LotArea< 12217.5 12 1.055214e+10 310238.30 *
##            123) LotArea>=12217.5 14 2.749692e+10 365437.10 *
##         31) BsmtUnfSF< 599 41 8.398221e+10 380371.50
##           62) BsmtFinSF1< 1270 18 3.566146e+10 347678.90 *
##           63) BsmtFinSF1>=1270 23 1.402603e+10 405957.00
##            126) GrLivArea< 1958 9 1.945442e+09 384827.70 *
##            127) GrLivArea>=1958 14 5.479498e+09 419540.20 *
```

```
# in-sample R-squared
in_sample_pred <- predict(final_model, newdata = train_ames)
SST_in <- sum((train_ames$SalePrice - mean(train_ames$SalePrice))^2)
SSR_in <- sum((in_sample_pred - mean(train_ames$SalePrice))^2)
R2_in_sample <- SSR_in / SST_in
cat("In-sample R-squared:", R2_in_sample, "\n")
```

```
## In-sample R-squared: 0.9105032
```

```
# out-of-sample R-squared from cross-validation results
out_of_sample_R2 <- max(tree_model_cv$results$Rsquared)
cat("Out-of-sample R-squared:", out_of_sample_R2, "\n")
```

```
## Out-of-sample R-squared: 0.7894255
```

RMSE was used to select the optimal model using the smallest value. The final value used for the model was cp = 5e-04 with n= 1972. This model has following stats: MAE of 21944.285, RMSE of 32280.79, in-sample R-squared: 0.9105032 , and out-of-sample R-squared of 0.7894255.

Part e

```
set.seed(15072)

# cross-validation control
control <- trainControl(method = "cv", number = 5)

# mtry tuning grid
mtry_values <- expand.grid(mtry = 1:73)

# train random forest with 80 trees (passed via ...)
rf_model_tuned <- train(
  SalePrice ~ .,
  data = train_ames,
  method = "rf",
  tuneGrid = mtry_values,
  trControl = control,
  importance = TRUE,
  ntree = 80
)

# display selected mtry
selected_mtry <- rf_model_tuned$bestTune$mtry
cat("Selected mtry value:", selected_mtry, "\n")
```

```
## Selected mtry value: 44
```

```
# in-sample R²
pred_train <- predict(rf_model_tuned, newdata = train_ames)
SSE_train <- sum((train_ames$SalePrice - pred_train)^2)
SST_train <- sum((train_ames$SalePrice - mean(train_ames$SalePrice))^2)
R2_train <- 1 - SSE_train / SST_train

# out-of-sample R² using test set mean
pred_test <- predict(rf_model_tuned, newdata = test_ames)
SSE_test <- sum((test_ames$SalePrice - pred_test)^2)
SST_test <- sum((test_ames$SalePrice - mean(test_ames$SalePrice))^2)
R2_test <- 1 - SSE_test / SST_test

cat("In-sample R²:", round(R2_train, 4), "\n")
```

```
## In-sample R²: 0.9811
```

```
cat("Out-of-sample R²:", round(R2_test, 4), "\n")
```

```
## Out-of-sample R²: 0.8733
```

Part f

Out of the four models constructed, I would recommend my model from part e - a random forest model with 80 trees, a nodesize of 25, and selected mtry value of 44. I believe this is the most robust model compared to the other linear regression and CART models. Out of all 4 models, this model had the highest out of sample R^2 at 0.8733, meaning that 87.33% of the variation in SalePrice from the test dataset could be explained by the model built on 44 variables chosen from the training dataset. The other models we looked at all had lower OOS R^2 at 0.83, 0.69, and 0.79 respectively for a, b, and d. Despite most of those models showing promising in sample R^2 (all above 0.75 and two around 0.90), they didn't perform as well with the test data, meaning that there could be some sort of overfitting occurring that isn't allowing for generalization towards unseen data. Our model in e had an in-sample R^2 of 0.9811. Also, I prefer my random forest model because it is very flexible compared to the other models. RF algorithms can effectively capture relationships and complex patterns within data by creating numerous decision trees, which can model non-linear boundaries and interactions between features. Specifically, with our mtry feature, at each node of a tree, the algorithm does not consider all available predictors. Instead, it randomly selects mtry number of predictors from the full set of predictors. This makes it less likely to select 2 highly correlated variables because one will be a more important predictor than the other (reducing the rmse more.) Unlike linear models that assume a straightforward relationship, the ensemble nature of a random forest allows it to learn intricate patterns that might be difficult for other algorithms to detect, making it a powerful and flexible tool for many machine learning tasks. The one thing that's not great about the RF is that it isn't interpretable. While individual trees are interpretable, the fact that we have a forest of trees with aggregate decision-making is difficult to follow. However, we can make plots and use techniques like feature importance to gain insights into the model's behavior and identify key drivers of its predictions.