Problem_1 - Riya

```
set.seed(15072)

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(caret)
```

```
## Loading required package: ggplot2

## Loading required package: lattice
```

```
library(rpart)
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(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v forcats   1.0.0     v stringr   1.5.1
## v lubridate 1.9.3     v tibble    3.2.1
## v purrr     1.0.2     v tidyr     1.3.1
## v readr     2.1.5
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x randomForest::combine() masks dplyr::combine()
## x dplyr::filter()         masks stats::filter()
## x dplyr::lag()            masks stats::lag()
## x purrr::lift()           masks caret::lift()
## x randomForest::margin()  masks ggplot2::margin()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts
 ↪  to become errors
```

```r
library(readr)
library(ggplot2)
library(olsrr)
```

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

```r
library(rpart.plot)
#install.packages("gbm")
library(gbm)
```

```
## Loaded gbm 2.2.2
## This version of gbm is no longer under development. Consider transitioning to gbm3,
 ↪  https://github.com/gbm-developers/gbm3
```

```r
#install.packages("Metrics")
library(Metrics)
```

```
##
## Attaching package: 'Metrics'
##
## The following objects are masked from 'package:caret':
##
##     precision, recall
```

```r
df <- read_csv("./ames.csv")
```

```
## Rows: 2818 Columns: 73
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (40): MSZoning, Street, Alley, LotShape, LandContour, LotConfig, LandSlo...
## dbl (33): SalePrice, LotFrontage, LotArea, YearBuilt, YearRemodAdd, MasVnrAr...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
head(df)
```

```
## # A tibble: 6 x 73
##   SalePrice MSZoning LotFrontage LotArea Street Alley    LotShape LandContour
##       <dbl> <chr>          <dbl>   <dbl> <chr>  <chr>    <chr>    <chr>
## 1    215000 RL               141   31770 Pave   No Alley IR1      Lvl
## 2    105000 Other             80   11622 Pave   No Alley Reg      Lvl
## 3    172000 RL                81   14267 Pave   No Alley IR1      Lvl
## 4    244000 RL                93   11160 Pave   No Alley Reg      Lvl
## 5    189900 RL                74   13830 Pave   No Alley IR1      Lvl
## 6    195500 RL                78    9978 Pave   No Alley IR1      Lvl
## # i 65 more variables: LotConfig <chr>, LandSlope <chr>, Neighborhood <chr>,
## #   Condition1 <chr>, Condition2 <chr>, BldgType <chr>, HouseStyle <chr>,
## #   YearBuilt <dbl>, YearRemodAdd <dbl>, RoofStyle <chr>, RoofMatl <chr>,
## #   Exterior1st <chr>, Exterior2nd <chr>, MasVnrType <chr>, MasVnrArea <dbl>,
## #   ExterQual <chr>, ExterCond <chr>, Foundation <chr>, BsmtQual <chr>,
## #   BsmtCond <chr>, BsmtExposure <chr>, BsmtFinType1 <chr>, BsmtFinSF1 <dbl>,
## #   BsmtFinType2 <chr>, BsmtFinSF2 <dbl>, BsmtUnfSF <dbl>, ...
```

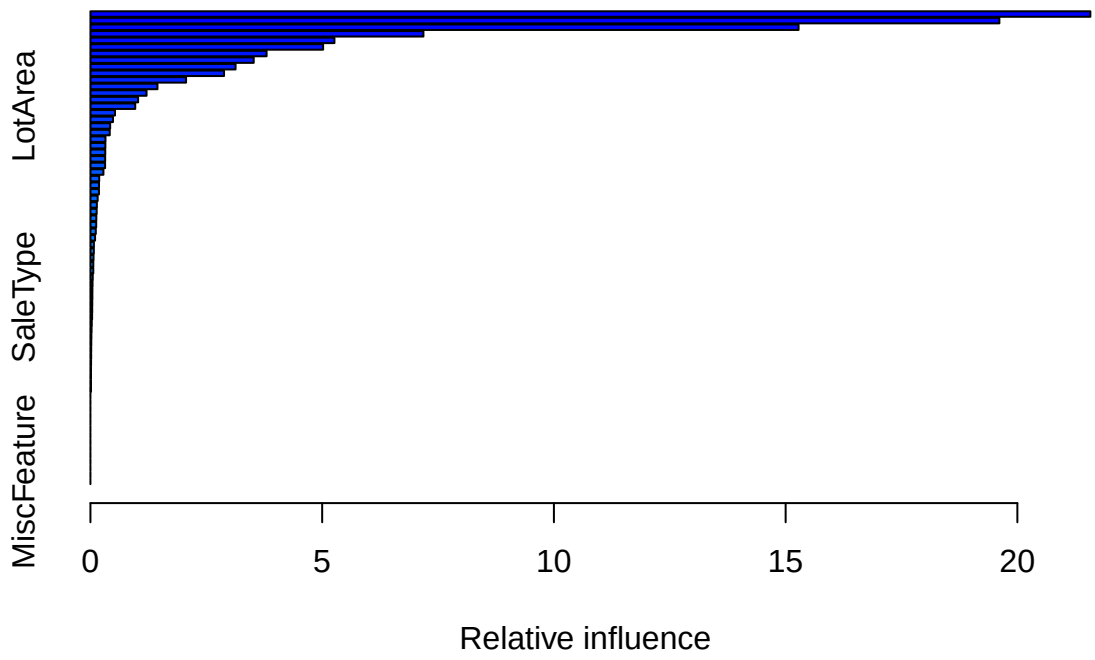
```
# Split the data into test and train (70% training, 30% testing)
set.seed(15072)
nrow = nrow(df)
df[sapply(df, is.character)] = lapply(df[sapply(df, is.character)], as.factor)
train_index = sample(1:nrow, size = 0.7*nrow)
train_ames = df[train_index, ]
test_ames = df[-train_index, ]
```

a) List the four out-of-sample R-squared values of the models you built from last time: linear regression; default-parameter CART; cp-optimized tree; random forest.

- For mod_linear_final: 0.8254482.
- Default parameter CART: 0.691.
- CP-optimized tree: 0.7894255.
- Random forest: 0.8733.

b) Fit an initial GBM model to the training data with the parameters listed below. Paste the code you used, the summary() of that model, and both its in-sample and out-of-sample R-squared.

```r
set.seed(15072)
# initial gb model
initial_model_gbm <- gbm(SalePrice ~ .,
                 data = train_ames,
                 distribution = "gaussian", # For regression
                 n.trees = 100,             # Number of boosting iterations
                 interaction.depth = 6,     # Maximum depth of each tree
                 shrinkage = 0.1,           # Learning rate
                 cv.folds = 10)             # Number of cross-validation folds
summary(initial_model_gbm)
```




```
##                       var     rel.inf
## ExterQual         ExterQual 21.57500906
## Neighborhood   Neighborhood 19.61203589
## GrLivArea         GrLivArea 15.27930103
## GarageCars       GarageCars  7.18472748
## TotalBsmtSF     TotalBsmtSF  5.26472265
## X1stFlrSF         X1stFlrSF  5.02098940
## GarageArea       GarageArea  3.80091271
## KitchenQual     KitchenQual  3.52308853
## BsmtFinSF1       BsmtFinSF1  3.13166299
## YearBuilt         YearBuilt  2.88267134
## BsmtQual           BsmtQual  2.06337170
## FireplaceQu     FireplaceQu  1.44654418
## GarageType       GarageType  1.21047724
```

```
## YearRemodAdd   YearRemodAdd  1.02854085
## LotArea             LotArea  0.96652059
## BsmtExposure   BsmtExposure  0.52969960
## GarageYrBlt     GarageYrBlt  0.48600454
## BsmtFinType1   BsmtFinType1  0.42593063
## X2ndFlrSF         X2ndFlrSF  0.41643240
## Fireplaces       Fireplaces  0.32456043
## LotFrontage     LotFrontage  0.32237367
## WoodDeckSF       WoodDeckSF  0.31971661
## Functional       Functional  0.31808188
## MasVnrArea       MasVnrArea  0.31652985
## CentralAir       CentralAir  0.28027193
## BsmtUnfSF         BsmtUnfSF  0.18915393
## GarageFinish   GarageFinish  0.18493680
## FullBath           FullBath  0.18346713
## Condition1       Condition1  0.15598825
## TotRmsAbvGrd   TotRmsAbvGrd  0.13887918
## BldgType           BldgType  0.13471589
## BsmtFullBath   BsmtFullBath  0.12714955
## KitchenAbvGr   KitchenAbvGr  0.12448714
## OpenPorchSF     OpenPorchSF  0.11559558
## BsmtCond           BsmtCond  0.10007086
## MoSold               MoSold  0.07452003
## BedroomAbvGr   BedroomAbvGr  0.07342685
## Exterior1st     Exterior1st  0.06656517
## YrSold               YrSold  0.06212389
## HeatingQC         HeatingQC  0.06183971
## LandContour     LandContour  0.04981984
## ScreenPorch     ScreenPorch  0.04525480
## Exterior2nd     Exterior2nd  0.04272438
## SaleType           SaleType  0.04180079
## LowQualFinSF   LowQualFinSF  0.03945218
## HouseStyle       HouseStyle  0.03840949
## EnclosedPorch EnclosedPorch  0.03618310
## PavedDrive       PavedDrive  0.02870736
## HalfBath           HalfBath  0.02396857
## LotConfig         LotConfig  0.02095558
## LandSlope         LandSlope  0.01845630
## MasVnrType       MasVnrType  0.01666029
## ExterCond         ExterCond  0.01627567
## MSZoning           MSZoning  0.01367114
## RoofMatl           RoofMatl  0.01217864
## X3SsnPorch       X3SsnPorch  0.01144115
## BsmtFinSF2       BsmtFinSF2  0.01071378
## BsmtHalfBath   BsmtHalfBath  0.01022977
## Street               Street  0.00000000
## Alley                 Alley  0.00000000
## LotShape           LotShape  0.00000000
## Condition2       Condition2  0.00000000
## RoofStyle         RoofStyle  0.00000000
## Foundation       Foundation  0.00000000
## BsmtFinType2   BsmtFinType2  0.00000000
## Heating             Heating  0.00000000
## Electrical       Electrical  0.00000000
## GarageQual       GarageQual  0.00000000
```

```
## PoolArea           PoolArea  0.00000000
## PoolQC               PoolQC  0.00000000
## Fence                 Fence  0.00000000
## MiscFeature     MiscFeature  0.00000000
```

```
pred_train = predict(initial_model_gbm, newdata=train_ames)
```

```
## Using 95 trees...
```

```
sse_train = sum((train_ames$SalePrice - pred_train)^2)
sst_train = sum((train_ames$SalePrice - mean(train_ames$SalePrice))^2)
insampler2 = 1-(sse_train/sst_train)

pred_test = predict(initial_model_gbm, newdata=test_ames)
```

```
## Using 95 trees...
```

```
sse_test = sum((test_ames$SalePrice - pred_test)^2)
sst_test = sum((test_ames$SalePrice - mean(test_ames$SalePrice))^2)
outofsampler2 = 1-(sse_test/sst_test)

cat("In sample r squared:", round(insampler2, 4), "\n")
```

```
## In sample r squared: 0.9516
```

```
cat("Out of sample r squared:", round(outofsampler2, 4), "\n")
```

```
## Out of sample r squared: 0.8813
```

- In sample r squared: 0.9516.
- Out of sample r squared: 0.8813.

c) For each of the following hyperparameters explain how these values affect the in-sample and out-of-sample R-squared values.

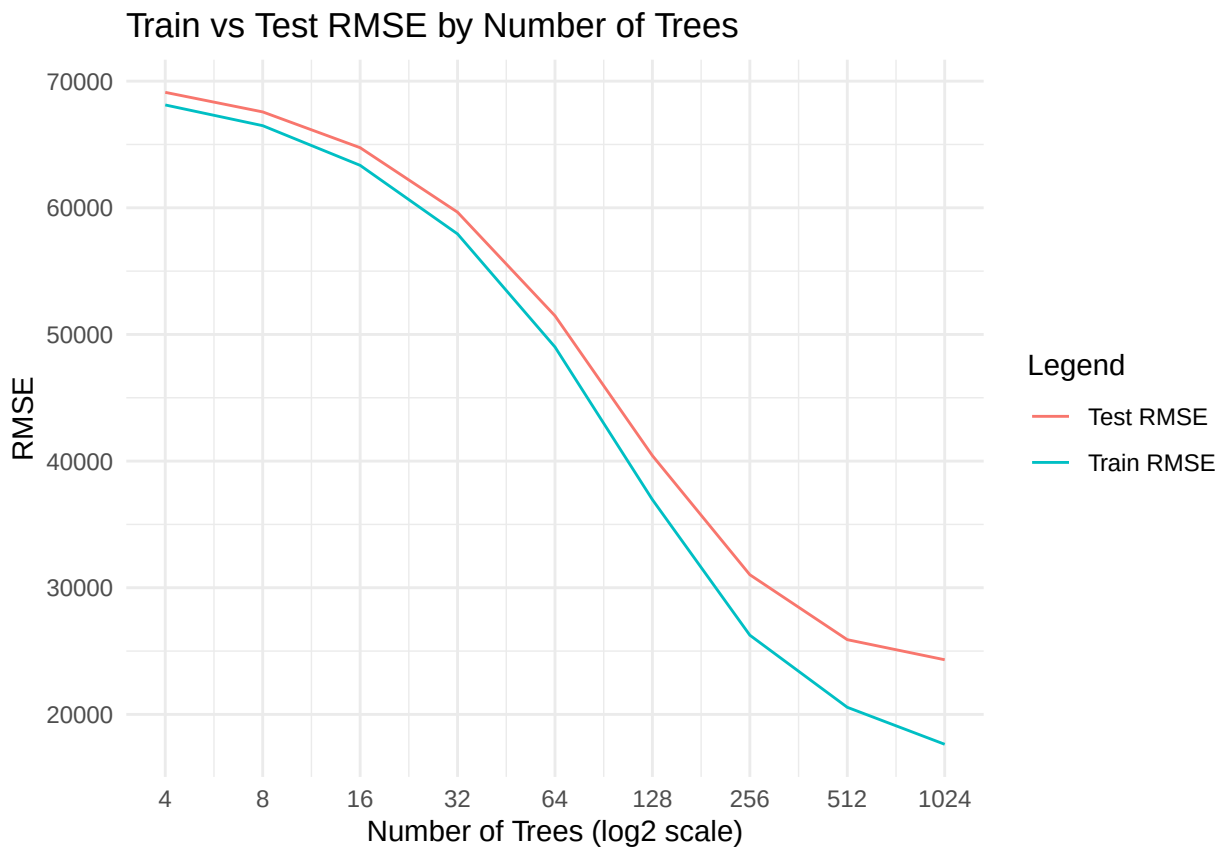
- Shrinkage is the learning rate, so if this number is high it means each tree has a strong influence, quickly fitting the training data and potentially over fitting. A smaller shrinkage dampens the effect of each tree, requiring more trees to reach the same level of fit. When shrinkage is large, in sample r squared is high and out of sample r squared is lower. When shrinkage is small, we get a lower r squared on the training data but a significantly better and more honest r squared on unseen data (out-of-sample R-squared).

- Interaction.depth is the maximum depth per tree, so if this number is too big we risk over fitting and if it's too small we risk under fitting. Generally having too big a number for interaction.depth when we train our model is bad because it'll over fit to the test set resulting in a very high in sample r squared but then it'll perform poorly on the new data in the test set resulting in a low out of sample r squared.

- N.trees gives us the number of boosting iterations, so the more iterations we have, generally speaking, the more our trees can learn and pinpoint improvement spots (high residual areas) from past residuals they have encountered. Having a higher n.trees hyper parameter improves both in and out of sample r squared (out of sample r squared will increase up to a certain point but then may decline if too many trees overfit).

d) Suppose instead that you set interaction.depth to 3 and shrinkage to 0.01 (and left all other hyperparameters as they were in part b). For n.trees = 4, 8, ..., 1024, compute the train RMSE (root mean square error) and the test RMSE. Plot the two RMSE lists on the same graph. Also include all code used for this part.

```r
set.seed(15072)

# tree counts
exponents <- 2:10
n.trees_list <- 2^exponents

# initialize RMSE storage lists
train_rmse <- numeric(length(n.trees_list))
test_rmse <- numeric(length(n.trees_list))

# loop over tree counts
for (i in seq_along(n.trees_list)) {
  n_trees <- n.trees_list[i]

  model <- gbm(SalePrice ~ .,
               data = train_ames,
               distribution = "gaussian",
               n.trees = n_trees,
               interaction.depth = 3,
               shrinkage = 0.01,
               cv.folds = 10,
               verbose = FALSE)

  # predictions
  train_pred <- predict(model, newdata = train_ames, n.trees = n_trees)
  test_pred <- predict(model, newdata = test_ames, n.trees = n_trees)

  # RMSE calculations
  train_rmse[i] <- rmse(train_ames$SalePrice, train_pred)
  test_rmse[i] <- rmse(test_ames$SalePrice, test_pred)
}

rmse_df <- data.frame(
  Trees = n.trees_list,
  Train_RMSE = train_rmse,
  Test_RMSE = test_rmse
)

ggplot(rmse_df, aes(x = Trees)) +
  geom_line(aes(y = Train_RMSE, color = "Train RMSE")) +
  geom_line(aes(y = Test_RMSE, color = "Test RMSE")) +
  scale_x_continuous(trans = "log2", breaks = n.trees_list) +
  labs(title = "Train vs Test RMSE by Number of Trees",
       x = "Number of Trees (log2 scale)",
       y = "RMSE",
       color = "Legend") +
  theme_minimal()
```



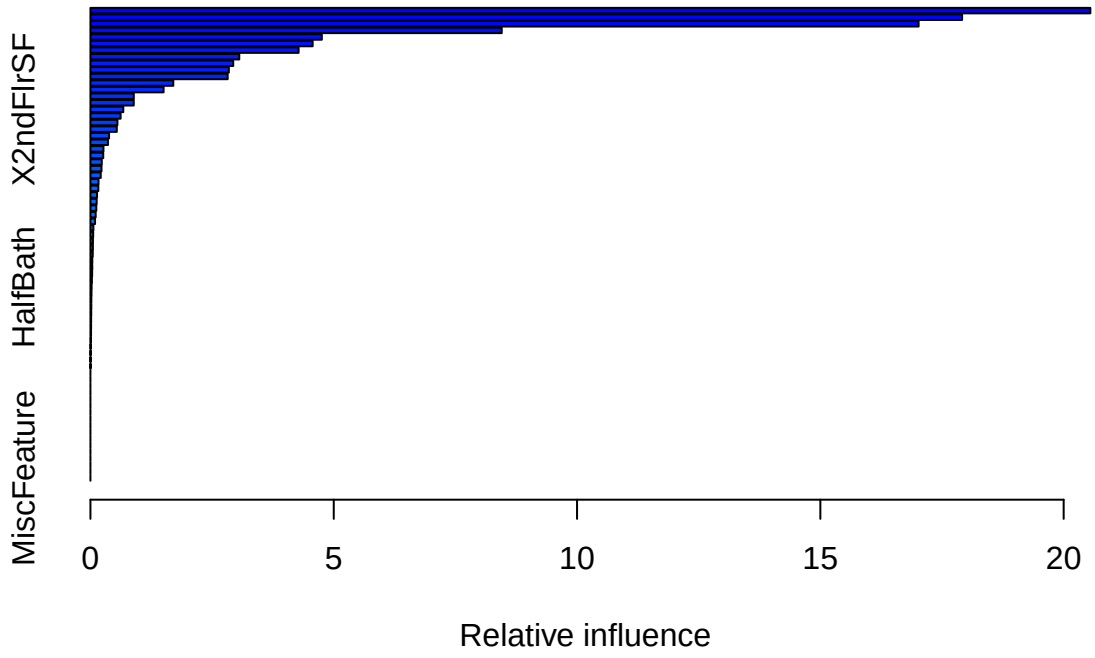
e) Which value of n.trees minimizes train set RMSE? test set RMSE? Are those two values the same or different? Which one is more important for model performance, and why? The value of n.trees that minimizes both train and test set RMSE is 1024. The one that is more important for model performance is test set RMSE because we want to know how our model performs on data it hasn't seen before. A high train set RMSE could just be the result of over fitting. If we really wanted to be be more robust in our techniques, we would have split our data into not just train/test sets, but train/test/validation sets to prevent information leakage when we go back and forth testing different hyper parameters. We would only use the test check to test the validity and accuracy of our final tuned model the final model.

f) Identify the patterns the graphs of train set RMSE and test set RMSE follow, and explain why.

Both the train and test RMSE decrease sharply at first because as the number of trees increases, the model can fit the data better and better – each additional tree corrects residuals from the previous ensemble. The test RMSE starts to flatten out a bit around 512-1024 trees, telling us that it has reached an approximate minimum in its RMSE improvement, suggesting minimal over fitting. This pattern makes sense because GBM builds trees based on the residuals of those coming before it. Having more trees means having more capacity to fit the training data, so we see a lower training RMSE. Also, because our shrinkage is set to 0.01 (pretty small), each tree contributes only a small adjustment. This slows learning and helps prevent over fitting, but requires many trees to reach optimal performance. All in all, we see that initially, test RAMSE drops as the model captures additional signal. However, after a certain point (512-1024 trees), those gains diminish because each of the later trees adds very little information in terms of residuals. The flattening of the RMSE curve here signals that the model is no longer improving generalization to unseen data points despite the fact that training RMSE continues to drop.

g) Consider the 6 different models you now have: the 4 from last deliverable, the initial GBM from part b, and your new optimal GBM from part e. Which one has the largest R-squared?

```
set.seed(15072)
#fitting the final model with 1024 trees as this was the best one based off the plot
 ↪  (lowest rmse test)
best_model <- gbm(SalePrice ~ .,
                  data = train_ames,
                  distribution = "gaussian",
                  n.trees = 1024,
                  interaction.depth = 3,
                  shrinkage = 0.01,
                  cv.folds = 10,
                  verbose = FALSE)

summary(best_model)
```




```
##                        var      rel.inf
## Neighborhood   Neighborhood 20.548534391
## GrLivArea         GrLivArea 17.913012441
## ExterQual         ExterQual 17.019096096
## TotalBsmtSF     TotalBsmtSF  8.452098387
## GarageCars       GarageCars  4.754806480
```

```
## YearBuilt         YearBuilt  4.566606769
## KitchenQual     KitchenQual  4.277585102
## BsmtQual           BsmtQual  3.058224316
## GarageArea       GarageArea  2.934236978
## X1stFlrSF         X1stFlrSF  2.843893173
## BsmtFinSF1       BsmtFinSF1  2.819938447
## FireplaceQu     FireplaceQu  1.702889832
## GarageType       GarageType  1.503103938
## LotArea             LotArea  0.890844657
## YearRemodAdd   YearRemodAdd  0.890001432
## X2ndFlrSF         X2ndFlrSF  0.675010241
## BsmtExposure   BsmtExposure  0.620578284
## GarageFinish   GarageFinish  0.554507665
## Fireplaces       Fireplaces  0.541557589
## BsmtFinType1   BsmtFinType1  0.383144003
## GarageYrBlt     GarageYrBlt  0.360073702
## CentralAir       CentralAir  0.267568273
## FullBath           FullBath  0.263167737
## LotFrontage     LotFrontage  0.232933556
## WoodDeckSF       WoodDeckSF  0.227542183
## Functional       Functional  0.212291556
## BsmtFullBath   BsmtFullBath  0.166059260
## Condition1       Condition1  0.162161874
## BldgType           BldgType  0.135228117
## TotRmsAbvGrd   TotRmsAbvGrd  0.128235738
## BsmtUnfSF         BsmtUnfSF  0.120493902
## MasVnrArea       MasVnrArea  0.107179580
## OpenPorchSF     OpenPorchSF  0.094820308
## BsmtCond           BsmtCond  0.061087063
## ScreenPorch     ScreenPorch  0.056707878
## SaleType           SaleType  0.051574209
## MoSold               MoSold  0.050514802
## LandContour     LandContour  0.047431964
## RoofMatl           RoofMatl  0.038420872
## HouseStyle       HouseStyle  0.037557500
## KitchenAbvGr   KitchenAbvGr  0.034802150
## LandSlope         LandSlope  0.029970925
## HalfBath           HalfBath  0.024310775
## HeatingQC         HeatingQC  0.021497319
## RoofStyle         RoofStyle  0.018903723
## LotShape           LotShape  0.018182180
## Exterior1st     Exterior1st  0.016333376
## EnclosedPorch EnclosedPorch  0.014874108
## LowQualFinSF   LowQualFinSF  0.013651463
## Exterior2nd     Exterior2nd  0.012626351
## BedroomAbvGr   BedroomAbvGr  0.010022676
## GarageQual       GarageQual  0.005269944
## ExterCond         ExterCond  0.003876065
## LotConfig         LotConfig  0.002972879
## YrSold               YrSold  0.001985771
## MSZoning           MSZoning  0.000000000
## Street               Street  0.000000000
## Alley                 Alley  0.000000000
## Condition2       Condition2  0.000000000
## MasVnrType       MasVnrType  0.000000000
```

```
## Foundation       Foundation  0.000000000
## BsmtFinType2   BsmtFinType2  0.000000000
## BsmtFinSF2       BsmtFinSF2  0.000000000
## Heating             Heating  0.000000000
## Electrical       Electrical  0.000000000
## BsmtHalfBath   BsmtHalfBath  0.000000000
## PavedDrive       PavedDrive  0.000000000
## X3SsnPorch       X3SsnPorch  0.000000000
## PoolArea           PoolArea  0.000000000
## PoolQC               PoolQC  0.000000000
## Fence                 Fence  0.000000000
## MiscFeature     MiscFeature  0.000000000
```

```
test_pred <- predict(best_model, newdata = test_ames, n.trees = 1024)
actual <- test_ames$SalePrice
r2_out_sample <- 1 - sum((actual - test_pred)^2) / sum((actual - mean(actual))^2)
print(paste("Out-of-sample R^2:", round(r2_out_sample, 4)))
```

```
## [1] "Out-of-sample R^2: 0.8811"
```

- For mod_linear_final: 0.8254482.
- Default parameter CART: 0.691.
- CP-optimized tree: 0.7894255.
- Random forest: 0.8733.
- Initial GBM from part b: 0.8813.
- New optimal GBM from part e: 0.8811.
- The model with the largest out of sample r squared is the initial GBM from part b with oos r squared of 0.8813. While one may think this is not ordinary as the model from part e was built more optimally, there are key hyper parameters that differ in the construction of both models. In part b, I chose to add cross validation with cv=10 to my model. So the model provided a more reliable estimate for performance on new, unseen data by training and testing on different subsets of the data. Also, the GBM was built with a deeper interaction depth (6 vs 3) and a higher learning rate (shrinkage of 0.1 vs 0.01). These choices allow the model to capture more complex interactions and adapt more aggressively to the training data. This can lead to better performance when the underlying signal is strong and the model is not overfitting. In contrast, part e's model—though more conservative—uses a smaller interaction depth and lower shrinkage, which slows learning and enforces stronger regularization. This setup is often preferred for stability and generalization, but in this case, the added regularization may have slightly limited the model's ability to fit subtle patterns in the data.Ultimately, both models perform very similarly, and the marginal difference in r squared reflects a delicate tradeoff between model complexity and regularization.