Appendix

Import Data

```
# Choose whether to reprocess data
reprocess = FALSE
reprocess = reprocess || !file.exists("../data/boston_data_raw.csv")
reprocess = reprocess || !file.exists("../data/boston_data.csv")
reprocess = reprocess || !file.exists("../data/boston_data_dummied.csv")

reprocess = reprocess || !file.exists("../data/boston_ddowntown.csv")
reprocess = reprocess || !file.exists("../data/boston_dairport.csv")
reprocess = reprocess || !file.exists("../data/boston_dboth.csv")

reprocess = reprocess || !file.exists("../data/boston_ddowntown_dummied.csv")
reprocess = reprocess || !file.exists("../data/boston_dairport_dummied.csv")
reprocess = reprocess || !file.exists("../data/boston_dboth_dummied.csv")

reprocess = reprocess || !file.exists("../data/boston_outliers.csv")

if (!reprocess) {
  # Read in existing data from file
  boston.data.raw <- read.csv("../data/boston_data_raw.csv", sep = ",", header=TRUE, na.strings=c("", "
  boston.data <- read.csv("../data/boston_data.csv", sep = ",", header=TRUE, na.strings=c("", " ", "NA"
  boston.dummied <- read.csv("../data/boston_data_dummied.csv", sep = ",", header=TRUE, na.strings=c(""

  boston.dboth <- read.csv("../data/boston_dboth.csv", sep = ",", header=TRUE, na.strings=c("", " ", "N
  boston.ddowntown<- read.csv("../data/boston_ddowntown.csv", sep = ",", header=TRUE, na.strings=c("",
  boston.dairport <- read.csv("../data/boston_dairport.csv", sep = ",", header=TRUE, na.strings=c("", "

  boston.dboth.dummied <- read.csv("../data/boston_dboth_dummied.csv", sep = ",", header=TRUE, na.strin
  boston.ddowntown.dummied <- read.csv("../data/boston_ddowntown_dummied.csv", sep = ",", header=TRUE,
  boston.dairport.dummied <- read.csv("../data/boston_dairport_dummied.csv", sep = ",", header=TRUE, na

  boston.outliers <- read.csv("../data/boston_outliers.csv", sep = ",", header=TRUE, na.strings=c("", "

  full.data <- read.csv("../data/listings.csv", sep = ",", header=TRUE, na.strings=c("", " ", "NA"))

} else {
  # Read in full dataset
  full.data <- read.csv("../data/listings.csv", sep = ",", header=TRUE, na.strings=c("", " ", "NA"))

  # Select features to keep
  features_to_keep <- c("host_is_superhost", "host_identity_verified", "neighbourhood_cleansed", "prope
  boston.data.raw <- full.data[ , features_to_keep, drop=FALSE]


  # Clean dataframe
  ## Omit NA values
  boston.data <- na.omit(boston.data.raw)
```

```r
## Change price to numeric
boston.data$price <- as.numeric(gsub(",", "", substr(boston.data$price, 2, length(boston.data$price) 

## Rename neighbourhood_cleansed to neighborhood
names(boston.data)[names(boston.data) == "neighbourhood_cleansed"] <- "neighborhood"

## Keep up to 95th percentile of price
value = quantile(boston.data$price, c(.95))[[1]]
boston.outliers <- boston.data[boston.data$price > value, ]
boston.data <- boston.data[boston.data$price <= value, ]



# Dummy categorical features
## Remove categorical columns to be re-added
categorical <- c("host_is_superhost", "host_identity_verified", "neighborhood", "property_type", "roo
boston.dummied <- boston.data %>% select(-one_of(categorical))

## host_is_superhost
boston.dummied <- cbind(boston.dummied, host_is_superhost=dummy(boston.data$host_is_superhost, sep="_

## host_identity_verified
boston.dummied <- cbind(boston.dummied, host_identity_verified=dummy(boston.data$host_identity_verifi

## instant_bookable
boston.dummied <- cbind(boston.dummied, instant_bookable=dummy(boston.data$instant_bookable, sep="_")

## is_business_travel_ready
boston.dummied <- cbind(boston.dummied, is_business_travel_ready=dummy(boston.data$is_business_travel_

## property_type
temp <- data.frame(dummy(boston.data$property_type))[ , -1]
boston.dummied <- cbind(boston.dummied, temp)

## room_type
temp <- data.frame(dummy(boston.data$room_type))[ , -1]
boston.dummied <- cbind(boston.dummied, temp)

## bed_type
temp <- data.frame(dummy(boston.data$bed_type))[ , -1]
boston.dummied <- cbind(boston.dummied, temp)

## cancellation_policy
temp <- data.frame(dummy(boston.data$cancellation_policy))[ , -1]
boston.dummied <- cbind(boston.dummied, temp)


# Construct distinct datasets

## Dataset with distance to downtown and airport
boston.dboth.dummied <- boston.dummied
boston.dboth.dummied$ddowntown <- 0
boston.dboth.dummied$dairport <- 0
```

```r
boston.dboth <- boston.data
boston.dboth$ddowntown <- 0
boston.dboth$dairport <- 0

### Calculate driving distance from property location to downtown/airport
ddowntown = hashmap(levels(boston.data$neighborhood), integer(length(levels(boston.data$neighborhood)
dairport = hashmap(levels(boston.data$neighborhood), integer(length(levels(boston.data$neighborhood))

for (i in 1:length(levels(boston.data$neighborhood))) {
  s <- levels(boston.data$neighborhood)[[i]]
  s2 <- paste(s, ", Boston MA")
  s2 <- gsub(" ", "+", s2, fixed=TRUE)
  ddowntown[[s]] <- gmapsdistance(origin=s2, destination="42.3555925+-71.0624982", mode="driving")[[2
  dairport[[s]] <- gmapsdistance(origin=s2, destination="42.3656171+-71.0117542", mode="driving")[[2]
}

for (i in 1:nrow(boston.dboth.dummied)) {
  boston.dboth.dummied[i, "ddowntown"] <- ddowntown[[boston.data$neighborhood[[i]]]]
  boston.dboth.dummied[i, "dairport"] <- dairport[[boston.data$neighborhood[[i]]]]

  boston.dboth[i, "ddowntown"] <- ddowntown[[boston.data$neighborhood[[i]]]]
  boston.dboth[i, "dairport"] <- dairport[[boston.data$neighborhood[[i]]]]
}

### Remove neighborhood columns
boston.dboth.dummied <- boston.dboth.dummied[ , !(names(boston.dboth.dummied) %in% c("neighborhood"))
boston.dboth <- boston.dboth[ , !(names(boston.dboth) %in% c("neighborhood"))]

## Dataset with distance to downtown only
boston.ddowntown.dummied <- boston.dboth.dummied[ , !(names(boston.dboth.dummied) %in% c("dairport"))
boston.ddowntown <- boston.dboth[ , !(names(boston.dboth) %in% c("dairport"))]

## Dataset with distance to airport only
boston.dairport.dummied <- boston.dboth.dummied[ , !(names(boston.dboth.dummied) %in% c("ddowntown"))
boston.dairport <- boston.dboth[ , !(names(boston.dboth) %in% c("ddowntown"))]

# Dummy neighborhood
## neighborhood
temp <- data.frame(dummy(boston.data$neighborhood))[ , -1]
boston.dummied <- cbind(boston.dummied, temp)


# Save data
write.csv(boston.data.raw, file="../data/boston_data_raw.csv")
write.csv(boston.data, file="../data/boston_data.csv")
write.csv(boston.dummied, file="../data/boston_data_dummied.csv")

write.csv(boston.ddowntown, file="../data/boston_ddowntown.csv")
write.csv(boston.dairport, file="../data/boston_dairport.csv")
write.csv(boston.dboth, file="../data/boston_dboth.csv")

write.csv(boston.ddowntown.dummied, file="../data/boston_ddowntown_dummied.csv")
write.csv(boston.dairport.dummied, file="../data/boston_dairport_dummied.csv")
```

```
  write.csv(boston.dboth.dummied, file="../data/boston_dboth_dummied.csv")

  write.csv(boston.outliers, file="../data/boston_outliers.csv")
}
```

Preliminary Data Analysis

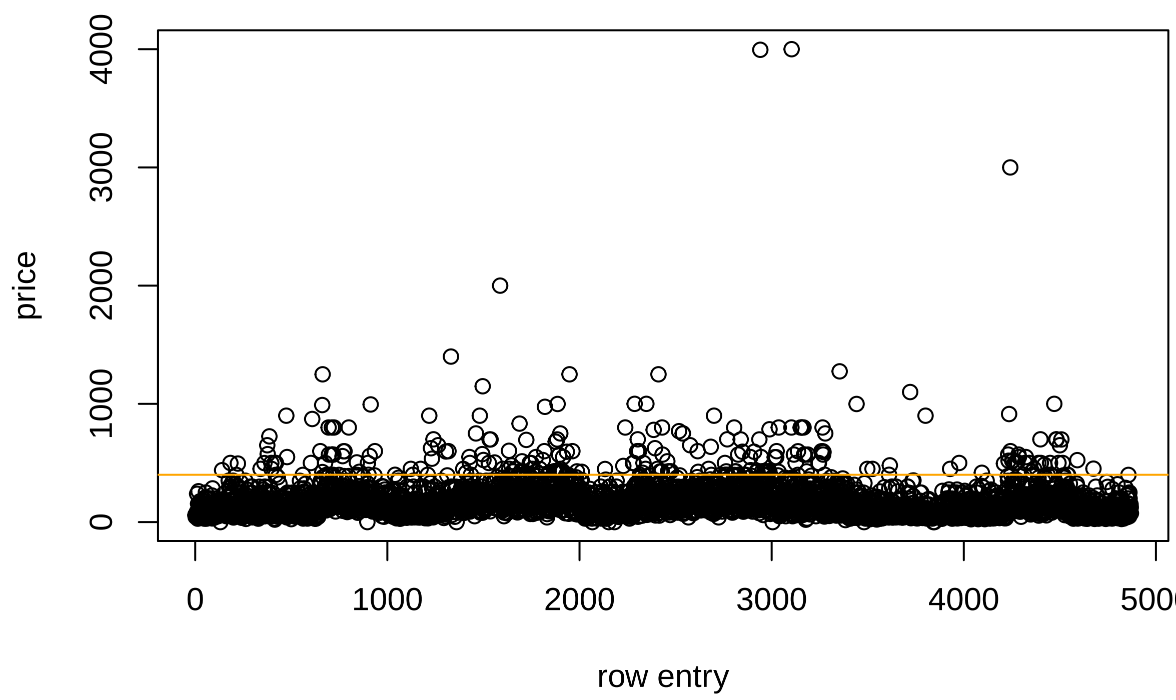
```
# Outlier investigation
summary(boston.data$price)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     0.0    80.0   133.0   148.8   199.0   400.0
```

```
sqrt(var(boston.data$price))
```

```
## [1] 84.57632
```

```
prices.with.outliers <- as.numeric(gsub(",", "", substr(boston.data.raw$price, 2, length(boston.data.raw
plot(prices.with.outliers, xlab="row entry", ylab="price")
abline(h=400, col="orange")
```

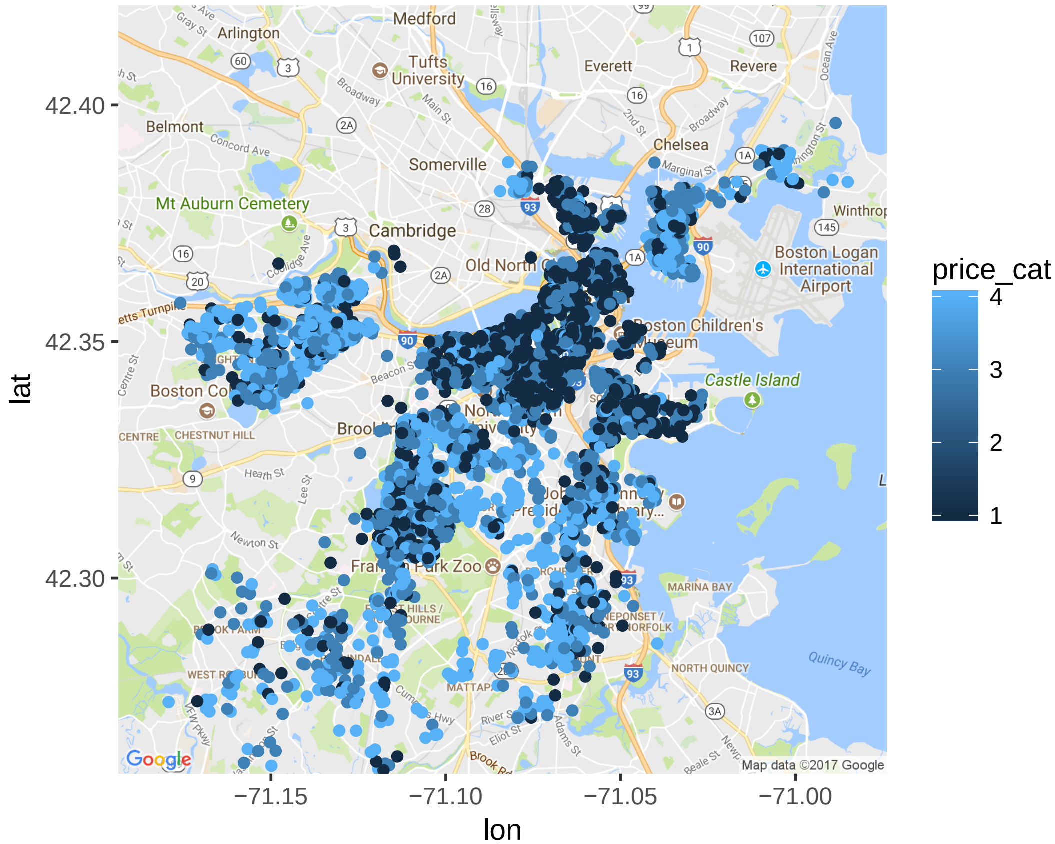



```
# Visualizing the dataset on a map

# changing data for map visualization
full.data$price <- as.numeric(gsub(",", "", substr(full.data$price, 2, length(full.data$price) - 1)))
```

```r
full.data <- full.data[!is.na(full.data$price),]
price_summary = summary(full.data$price)

# fetching data for map visualization
states <- map_data("state")
ma_df <- subset(states, region == "massachusetts")
counties <- map_data("county")
ma_county <- subset(counties, region == "massachusetts")
ma_base <- ggplot(data = ma_df, mapping = aes(x = long, y = lat, group = group)) + coord_fixed(1.3) +  g
ma_city<-ma_base + geom_polygon(data = ma_county, fill = NA, color = "white") +  geom_polygon(color = "b
map = get_map(location <- c(mean(full.data$longitude), mean(full.data$latitude)), zoom = 12, source = "g
```

```
## Map from URL : http://maps.googleapis.com/maps/api/staticmap?center=42.339999,-71.083943&zoom=12&size
```

```r
# setting price categories
for (i in 1:nrow(full.data))
{
  if (full.data$price[i]<price_summary[2])
  {full.data$price_cat[i]=4}
  if (full.data$price[i]>price_summary[2]&full.data$price[i]<price_summary[4])
  {full.data$price_cat[i]=3}
  if (full.data$price[i]>price_summary[4]&full.data$price[i]<price_summary[5])
  {full.data$price_cat[i]=2}
  if (price_summary[4]<full.data$price[i])
  {full.data$price_cat[i]=1}
}

# plot map
ggmap(map) + geom_point(aes(x=longitude,y=latitude,group=price_cat,color=price_cat),data=full.data)
```



Count Missing Values

```
sum(is.na(boston.data.raw))
```

```
## [1] 14
```

Divide data into training and validation sets

```
# Sample indices for training and validations sets
num_rows <- nrow(boston.data)

# 55% training
training <- sample(1:num_rows, floor(0.55 * num_rows))
rest <- (1:num_rows)[-training]

# 15% model selection
model_selection <- sample(rest, floor(0.15 * num_rows))
rest <- (1:num_rows)[-c(training, model_selection)]

# 15% validation #1
validation_1 <- sample(rest, floor(0.15 * num_rows))
rest <- (1:num_rows)[-c(training, model_selection, validation_1)]
```

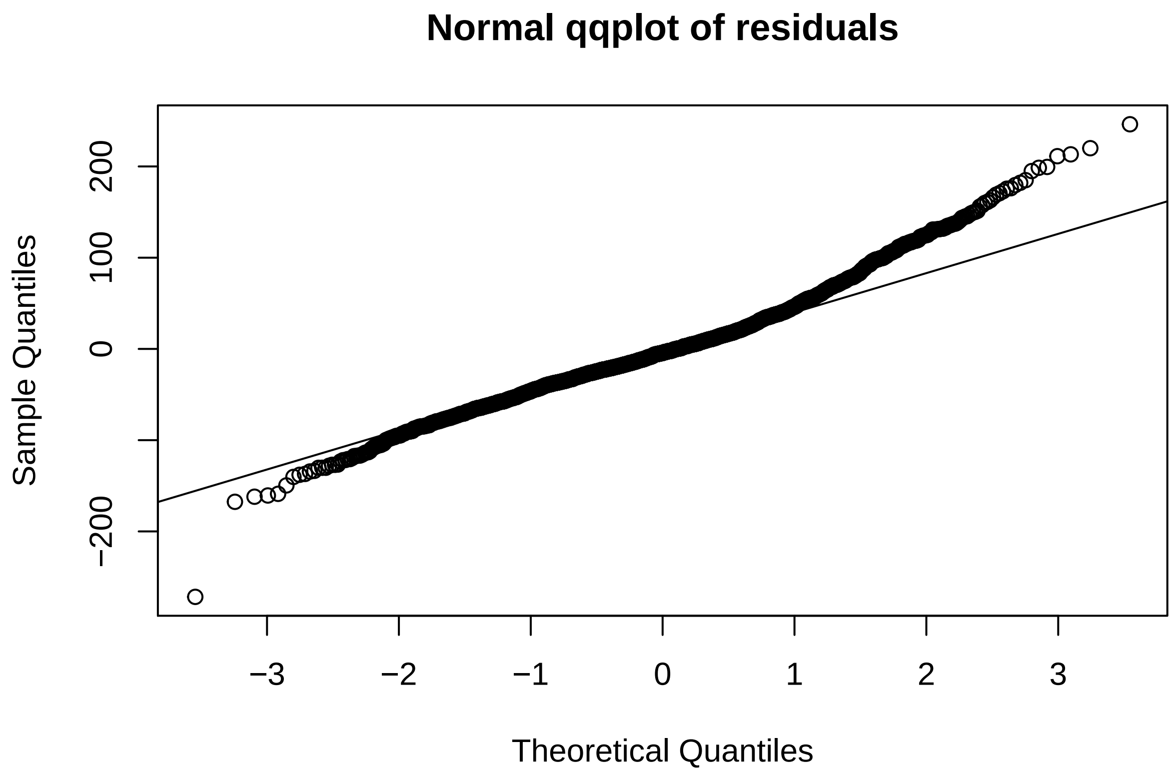
```r
# 15% validation #2
validation_2 <- sample(rest, floor(0.15 * num_rows))
rest <- (1:num_rows)[-c(training, model_selection, validation_1, validation_2)]

# Set datasets for each transformation
boston.data.training <- boston.data[training, ]
boston.data.model_selection <- boston.data[model_selection, ]
boston.data.validation_1 <- boston.data[validation_1, ]
boston.data.validation_2 <- boston.data[validation_2, ]
boston.data.model_selection.test <- boston.data.model_selection[ , "price"]
boston.data.validation_1.test <- boston.data.validation_1[ , "price"]
boston.data.validation_2.test <- boston.data.validation_2[ , "price"]

boston.dboth.training <- boston.dboth[training, ]
boston.dboth.model_selection <- boston.dboth[model_selection, ]
boston.dboth.validation_1 <- boston.dboth[validation_1, ]
boston.dboth.validation_2 <- boston.dboth[validation_2, ]
boston.dboth.model_selection.test <- boston.dboth.model_selection[ , "price"]
boston.dboth.validation_1.test <- boston.dboth.validation_1[ , "price"]
boston.dboth.validation_2.test <- boston.dboth.validation_2[ , "price"]

boston.ddowntown.training <- boston.ddowntown[training, ]
boston.ddowntown.model_selection <- boston.ddowntown[model_selection, ]
boston.ddowntown.validation_1 <- boston.ddowntown[validation_1, ]
boston.ddowntown.validation_2 <- boston.ddowntown[validation_2, ]
boston.ddowntown.model_selection.test <- boston.ddowntown.model_selection[ , "price"]
boston.ddowntown.validation_1.test <- boston.ddowntown.validation_1[ , "price"]
boston.ddowntown.validation_2.test <- boston.ddowntown.validation_2[ , "price"]

boston.dairport.training <- boston.dairport[training, ]
boston.dairport.model_selection <- boston.dairport[model_selection, ]
boston.dairport.validation_1 <- boston.dairport[validation_1, ]
boston.dairport.validation_2 <- boston.dairport[validation_2, ]
boston.dairport.model_selection.test <- boston.dairport.model_selection[ , "price"]
boston.dairport.validation_1.test <- boston.dairport.validation_1[ , "price"]
boston.dairport.validation_2.test <- boston.dairport.validation_2[ , "price"]


#Dummied
boston.dummied.training <- boston.dummied[training, ][,-1]
boston.dummied.model_selection <- boston.dummied[model_selection, ][,-1]
boston.dummied.validation_1 <- boston.dummied[validation_1, ][,-1]
boston.dummied.validation_2 <- boston.dummied[validation_2, ][,-1]
boston.dummied.model_selection.test <- boston.dummied.model_selection[ , "price"]
boston.dummied.validation_1.test <- boston.dummied.validation_1[ , "price"]
boston.dummied.validation_2.test <- boston.dummied.validation_2[ , "price"]

boston.dboth.dummied.training <- boston.dboth.dummied[training, ][,-1]
boston.dboth.dummied.model_selection <- boston.dboth.dummied[model_selection, ][,-1]
boston.dboth.dummied.validation_1 <- boston.dboth.dummied[validation_1, ][,-1]
boston.dboth.dummied.validation_2 <- boston.dboth.dummied[validation_2, ][,-1]
boston.dboth.dummied.model_selection.test <- boston.dboth.dummied.model_selection[ , "price"]
boston.dboth.dummied.validation_1.test <- boston.dboth.dummied.validation_1[ , "price"]
```

```r
boston.dboth.dummied.validation_2.test <- boston.dboth.dummied.validation_2[ , "price"]

boston.ddowntown.dummied.training <- boston.ddowntown.dummied[training, ][,-1]
boston.ddowntown.dummied.model_selection <- boston.ddowntown.dummied[model_selection, ][,-1]
boston.ddowntown.dummied.validation_1 <- boston.ddowntown.dummied[validation_1, ][,-1]
boston.ddowntown.dummied.validation_2 <- boston.ddowntown.dummied[validation_2, ][,-1]
boston.ddowntown.dummied.model_selection.test <- boston.ddowntown.dummied.model_selection[ , "price"]
boston.ddowntown.dummied.validation_1.test <- boston.ddowntown.dummied.validation_1[ , "price"]
boston.ddowntown.dummied.validation_2.test <- boston.ddowntown.dummied.validation_2[ , "price"]

boston.dairport.dummied.training <- boston.dairport.dummied[training, ][,-1]
boston.dairport.dummied.model_selection <- boston.dairport.dummied[model_selection, ][,-1]
boston.dairport.dummied.validation_1 <- boston.dairport.dummied[validation_1, ][,-1]
boston.dairport.dummied.validation_2 <- boston.dairport.dummied[validation_2, ][,-1]
boston.dairport.dummied.model_selection.test <- boston.dairport.dummied.model_selection[ , "price"]
boston.dairport.dummied.validation_1.test <- boston.dairport.dummied.validation_1[ , "price"]
boston.dairport.dummied.validation_2.test <- boston.dairport.dummied.validation_2[ , "price"]
```

Linear Regression

QQ Plot

```r
lm_train <- lm(price~.,data = boston.dummied.training)
qqnorm(lm_train$residuals, main = "Normal qqplot of residuals")
qqline(lm_train$residuals)
```




```r
summary(lm_train)
```

```
##
## Call:
## lm(formula = price ~ ., data = boston.dummied.training)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -271.727  -32.041   -4.277   26.032  246.226
##
## Coefficients:
##                                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)                          77.82281   13.34716   5.831 6.24e-09
## accommodates                          6.64028    1.26379   5.254 1.61e-07
## bathrooms                             9.53191    2.78692   3.420 0.000636
## bedrooms                             21.74546    2.17508   9.998  < 2e-16
## beds                                 -1.27594    1.78775  -0.714 0.475471
## guests_included                       5.97530    1.14571   5.215 1.99e-07
## minimum_nights                       -0.55959    0.17343  -3.227 0.001269
## number_of_reviews                    -0.07602    0.02955  -2.573 0.010154
## host_is_superhost                     4.24667    2.89429   1.467 0.142433
## host_identity_verified               -4.00203    2.29749  -1.742 0.081648
## instant_bookable                    -15.28341    2.32885  -6.563 6.42e-11
## is_business_travel_ready              5.57453    3.43213   1.624 0.104456
## property_type.Bed...Breakfast        15.91293   14.06906   1.131 0.258140
## property_type.Boat                   27.01379   24.19628   1.116 0.264340
```

```
## property_type.Boutique.hotel         -53.49514   31.67050  -1.689 0.091323
## property_type.Condominium             14.10607    3.77584   3.736 0.000191
## property_type.Dorm                   -23.66661   53.28921  -0.444 0.656997
## property_type.Guest.suite             33.07917   21.86623   1.513 0.130459
## property_type.Guesthouse              93.50281   30.78664   3.037 0.002413
## property_type.Hostel                 -36.57018   54.36344  -0.673 0.501202
## property_type.House                    4.97656    3.42256   1.454 0.146060
## property_type.In.law                 -21.41527   24.08282  -0.889 0.373963
## property_type.Loft                    28.03977   12.09199   2.319 0.020483
## property_type.Other                   56.32753    9.72999   5.789 7.97e-09
## property_type.Serviced.apartment     -34.30252   53.30508  -0.644 0.519951
## property_type.Timeshare              221.67984   53.34252   4.156 3.35e-05
## property_type.Townhouse               11.63049    8.81182   1.320 0.186999
## property_type.Villa                   23.95943   20.28778   1.181 0.237725
## room_type.Private.room               -59.96130    3.18379 -18.833  < 2e-16
## room_type.Shared.room                -69.55790   10.36401  -6.711 2.38e-11
## bed_type.Couch                        10.82588   29.59114   0.366 0.714509
## bed_type.Futon                         9.04917   16.93452   0.534 0.593139
## bed_type.Pull.out.Sofa                 5.81692   18.84600   0.309 0.757610
## bed_type.Real.Bed                      2.63486   11.64667   0.226 0.821039
## cancellation_policy.moderate           7.41513    3.18136   2.331 0.019844
## cancellation_policy.strict            -8.04279    2.80355  -2.869 0.004155
## cancellation_policy.super_strict_30   41.86365   14.10633   2.968 0.003029
## cancellation_policy.super_strict_60  101.02557   53.46241   1.890 0.058921
## neighborhood.Back.Bay                 83.21054    5.94132  14.005  < 2e-16
## neighborhood.Bay.Village              50.58238   14.93415   3.387 0.000718
## neighborhood.Beacon.Hill              71.88781    6.29898  11.413  < 2e-16
## neighborhood.Brighton                  7.29242    5.97593   1.220 0.222468
## neighborhood.Charlestown              56.17710    7.88925   7.121 1.40e-12
## neighborhood.Chinatown                49.62942    8.20624   6.048 1.69e-09
## neighborhood.Dorchester                5.68429    5.78911   0.982 0.326248
## neighborhood.Downtown                 73.80523    6.37621  11.575  < 2e-16
## neighborhood.East.Boston              10.85957    6.22746   1.744 0.081314
## neighborhood.Fenway                   42.65976    5.93631   7.186 8.77e-13
## neighborhood.Hyde.Park                -9.66046   11.57767  -0.834 0.404133
## neighborhood.Jamaica.Plain            12.42193    5.61299   2.213 0.026984
## neighborhood.Leather.District        106.30611   27.64638   3.845 0.000123
## neighborhood.Longwood.Medical.Area    59.90400   27.05814   2.214 0.026926
## neighborhood.Mattapan                 -9.92169   13.28813  -0.747 0.455340
## neighborhood.Mission.Hill             13.09720    7.55366   1.734 0.083062
## neighborhood.North.End                26.34956    7.21092   3.654 0.000263
## neighborhood.Roslindale              -14.09843    8.22510  -1.714 0.086640
## neighborhood.Roxbury                   9.14193    6.41293   1.426 0.154125
## neighborhood.South.Boston             33.23096    6.31483   5.262 1.54e-07
## neighborhood.South.Boston.Waterfront  91.60338   10.19628   8.984  < 2e-16
## neighborhood.South.End                62.53158    5.92833  10.548  < 2e-16
## neighborhood.West.End                 49.06793   11.14381   4.403 1.11e-05
## neighborhood.West.Roxbury             -2.82290    9.70120  -0.291 0.771088
##
## (Intercept)                          ***
## accommodates                         ***
## bathrooms                            ***
## bedrooms                             ***
## beds
```

```
## guests_included                      ***
## minimum_nights                       **
## number_of_reviews                    *
## host_is_superhost
## host_identity_verified               .
## instant_bookable                     ***
## is_business_travel_ready
## property_type.Bed...Breakfast
## property_type.Boat
## property_type.Boutique.hotel         .
## property_type.Condominium            ***
## property_type.Dorm
## property_type.Guest.suite
## property_type.Guesthouse             **
## property_type.Hostel
## property_type.House
## property_type.In.law
## property_type.Loft                   *
## property_type.Other                  ***
## property_type.Serviced.apartment
## property_type.Timeshare              ***
## property_type.Townhouse
## property_type.Villa
## room_type.Private.room               ***
## room_type.Shared.room                ***
## bed_type.Couch
## bed_type.Futon
## bed_type.Pull.out.Sofa
## bed_type.Real.Bed
## cancellation_policy.moderate         *
## cancellation_policy.strict           **
## cancellation_policy.super_strict_30  **
## cancellation_policy.super_strict_60  .
## neighborhood.Back.Bay                ***
## neighborhood.Bay.Village             ***
## neighborhood.Beacon.Hill             ***
## neighborhood.Brighton
## neighborhood.Charlestown             ***
## neighborhood.Chinatown               ***
## neighborhood.Dorchester
## neighborhood.Downtown                ***
## neighborhood.East.Boston             .
## neighborhood.Fenway                  ***
## neighborhood.Hyde.Park
## neighborhood.Jamaica.Plain           *
## neighborhood.Leather.District        ***
## neighborhood.Longwood.Medical.Area   *
## neighborhood.Mattapan
## neighborhood.Mission.Hill            .
## neighborhood.North.End               ***
## neighborhood.Roslindale              .
## neighborhood.Roxbury
## neighborhood.South.Boston            ***
## neighborhood.South.Boston.Waterfront ***
```

```
## neighborhood.South.End               ***
## neighborhood.West.End                ***
## neighborhood.West.Roxbury
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 53.01 on 2477 degrees of freedom
## Multiple R-squared:  0.6145, Adjusted R-squared:  0.605
## F-statistic: 64.74 on 61 and 2477 DF,  p-value: < 2.2e-16
```

We can see that the assumption the variables are linear are somewhat valid, except from the long tails at both ends.

```r
library(leaps)
regfit.full <- regsubsets(price~., data = boston.dummied.training, really.big = T)
reg.summary <- summary(regfit.full)
reg.summary
```

```
## Subset selection object
## Call: regsubsets.formula(price ~ ., data = boston.dummied.training,
##     really.big = T)
## 61 Variables  (and intercept)
##                                       Forced in Forced out
## accommodates                              FALSE      FALSE
## bathrooms                                 FALSE      FALSE
## bedrooms                                  FALSE      FALSE
## beds                                      FALSE      FALSE
## guests_included                           FALSE      FALSE
## minimum_nights                            FALSE      FALSE
## number_of_reviews                         FALSE      FALSE
## host_is_superhost                         FALSE      FALSE
## host_identity_verified                    FALSE      FALSE
## instant_bookable                          FALSE      FALSE
## is_business_travel_ready                  FALSE      FALSE
## property_type.Bed...Breakfast             FALSE      FALSE
## property_type.Boat                        FALSE      FALSE
## property_type.Boutique.hotel              FALSE      FALSE
## property_type.Condominium                 FALSE      FALSE
## property_type.Dorm                        FALSE      FALSE
## property_type.Guest.suite                 FALSE      FALSE
## property_type.Guesthouse                  FALSE      FALSE
## property_type.Hostel                      FALSE      FALSE
## property_type.House                       FALSE      FALSE
## property_type.In.law                      FALSE      FALSE
## property_type.Loft                        FALSE      FALSE
## property_type.Other                       FALSE      FALSE
## property_type.Serviced.apartment          FALSE      FALSE
## property_type.Timeshare                   FALSE      FALSE
## property_type.Townhouse                   FALSE      FALSE
## property_type.Villa                       FALSE      FALSE
## room_type.Private.room                    FALSE      FALSE
## room_type.Shared.room                     FALSE      FALSE
## bed_type.Couch                            FALSE      FALSE
## bed_type.Futon                            FALSE      FALSE
## bed_type.Pull.out.Sofa                    FALSE      FALSE
```

```
## bed_type.Real.Bed                         FALSE      FALSE
## cancellation_policy.moderate              FALSE      FALSE
## cancellation_policy.strict                FALSE      FALSE
## cancellation_policy.super_strict_30       FALSE      FALSE
## cancellation_policy.super_strict_60       FALSE      FALSE
## neighborhood.Back.Bay                     FALSE      FALSE
## neighborhood.Bay.Village                  FALSE      FALSE
## neighborhood.Beacon.Hill                  FALSE      FALSE
## neighborhood.Brighton                     FALSE      FALSE
## neighborhood.Charlestown                  FALSE      FALSE
## neighborhood.Chinatown                    FALSE      FALSE
## neighborhood.Dorchester                   FALSE      FALSE
## neighborhood.Downtown                     FALSE      FALSE
## neighborhood.East.Boston                  FALSE      FALSE
## neighborhood.Fenway                       FALSE      FALSE
## neighborhood.Hyde.Park                    FALSE      FALSE
## neighborhood.Jamaica.Plain                FALSE      FALSE
## neighborhood.Leather.District             FALSE      FALSE
## neighborhood.Longwood.Medical.Area        FALSE      FALSE
## neighborhood.Mattapan                     FALSE      FALSE
## neighborhood.Mission.Hill                 FALSE      FALSE
## neighborhood.North.End                    FALSE      FALSE
## neighborhood.Roslindale                   FALSE      FALSE
## neighborhood.Roxbury                      FALSE      FALSE
## neighborhood.South.Boston                 FALSE      FALSE
## neighborhood.South.Boston.Waterfront      FALSE      FALSE
## neighborhood.South.End                    FALSE      FALSE
## neighborhood.West.End                     FALSE      FALSE
## neighborhood.West.Roxbury                 FALSE      FALSE
## 1 subsets of each size up to 8
## Selection Algorithm: exhaustive
##          accommodates bathrooms bedrooms beds guests_included
## 1  ( 1 ) " "          " "       " "      " "  " "
## 2  ( 1 ) "*"          " "       " "      " "  " "
## 3  ( 1 ) "*"          " "       " "      " "  " "
## 4  ( 1 ) " "          " "       "*"      " "  " "
## 5  ( 1 ) " "          " "       "*"      " "  " "
## 6  ( 1 ) " "          " "       "*"      " "  " "
## 7  ( 1 ) " "          " "       "*"      " "  " "
## 8  ( 1 ) "*"          " "       "*"      " "  " "
##          minimum_nights number_of_reviews host_is_superhost
## 1  ( 1 ) " "            " "               " "
## 2  ( 1 ) " "            " "               " "
## 3  ( 1 ) " "            " "               " "
## 4  ( 1 ) " "            " "               " "
## 5  ( 1 ) " "            " "               " "
## 6  ( 1 ) " "            " "               " "
## 7  ( 1 ) " "            " "               " "
## 8  ( 1 ) " "            " "               " "
##          host_identity_verified instant_bookable is_business_travel_ready
## 1  ( 1 ) " "                    " "              " "
## 2  ( 1 ) " "                    " "              " "
## 3  ( 1 ) " "                    " "              " "
## 4  ( 1 ) " "                    " "              " "
```

```
## 5  ( 1 ) " "                    " "              " "
## 6  ( 1 ) " "                    " "              " "
## 7  ( 1 ) " "                    " "              " "
## 8  ( 1 ) " "                    " "              " "
##          property_type.Bed...Breakfast property_type.Boat
## 1  ( 1 ) " "                          " "
## 2  ( 1 ) " "                          " "
## 3  ( 1 ) " "                          " "
## 4  ( 1 ) " "                          " "
## 5  ( 1 ) " "                          " "
## 6  ( 1 ) " "                          " "
## 7  ( 1 ) " "                          " "
## 8  ( 1 ) " "                          " "
##          property_type.Boutique.hotel property_type.Condominium
## 1  ( 1 ) " "                         " "
## 2  ( 1 ) " "                         " "
## 3  ( 1 ) " "                         " "
## 4  ( 1 ) " "                         " "
## 5  ( 1 ) " "                         " "
## 6  ( 1 ) " "                         " "
## 7  ( 1 ) " "                         " "
## 8  ( 1 ) " "                         " "
##          property_type.Dorm property_type.Guest.suite
## 1  ( 1 ) " "               " "
## 2  ( 1 ) " "               " "
## 3  ( 1 ) " "               " "
## 4  ( 1 ) " "               " "
## 5  ( 1 ) " "               " "
## 6  ( 1 ) " "               " "
## 7  ( 1 ) " "               " "
## 8  ( 1 ) " "               " "
##          property_type.Guesthouse property_type.Hostel property_type.House
## 1  ( 1 ) " "                     " "                  " "
## 2  ( 1 ) " "                     " "                  " "
## 3  ( 1 ) " "                     " "                  " "
## 4  ( 1 ) " "                     " "                  " "
## 5  ( 1 ) " "                     " "                  " "
## 6  ( 1 ) " "                     " "                  " "
## 7  ( 1 ) " "                     " "                  " "
## 8  ( 1 ) " "                     " "                  " "
##          property_type.In.law property_type.Loft property_type.Other
## 1  ( 1 ) " "                 " "                " "
## 2  ( 1 ) " "                 " "                " "
## 3  ( 1 ) " "                 " "                " "
## 4  ( 1 ) " "                 " "                " "
## 5  ( 1 ) " "                 " "                " "
## 6  ( 1 ) " "                 " "                " "
## 7  ( 1 ) " "                 " "                " "
## 8  ( 1 ) " "                 " "                " "
##          property_type.Serviced.apartment property_type.Timeshare
## 1  ( 1 ) " "                             " "
## 2  ( 1 ) " "                             " "
## 3  ( 1 ) " "                             " "
## 4  ( 1 ) " "                             " "
```

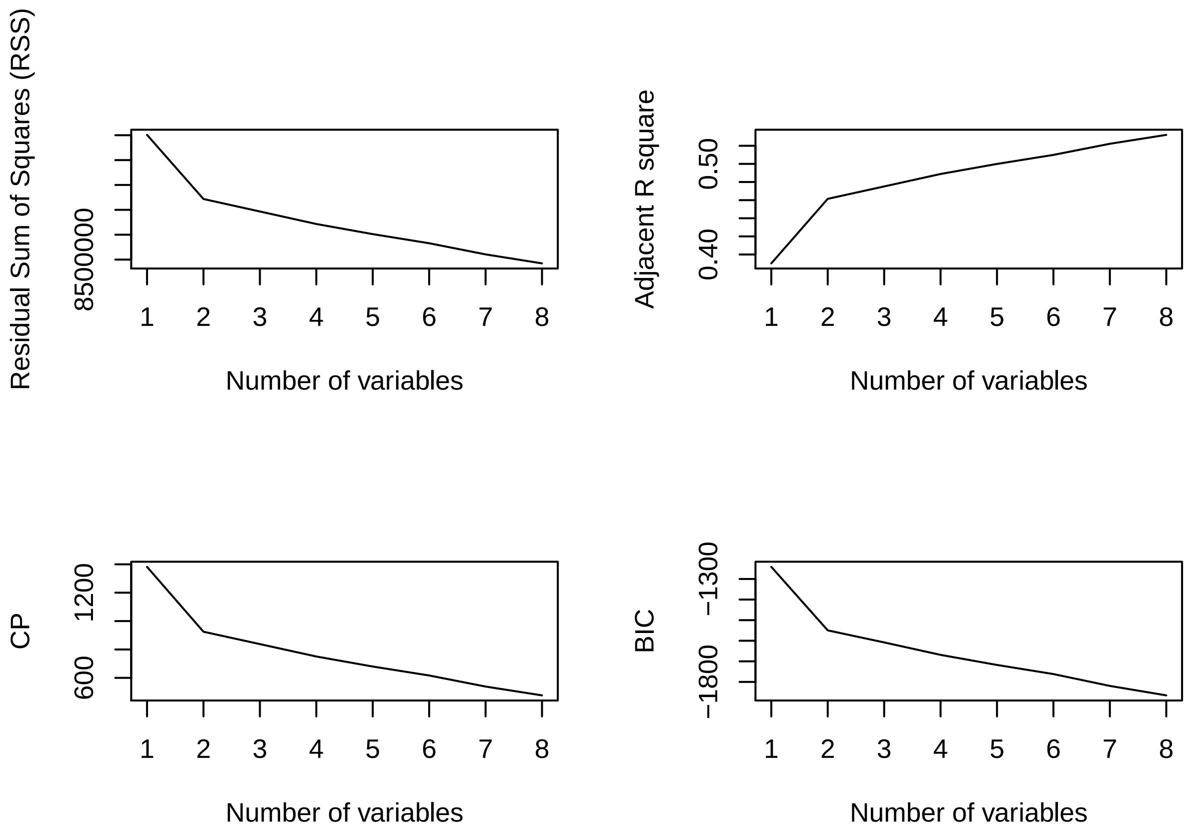
```
## 5  ( 1 ) " "                              " "
## 6  ( 1 ) " "                              " "
## 7  ( 1 ) " "                              " "
## 8  ( 1 ) " "                              " "
##           property_type.Townhouse property_type.Villa
## 1  ( 1 ) " "                     " "
## 2  ( 1 ) " "                     " "
## 3  ( 1 ) " "                     " "
## 4  ( 1 ) " "                     " "
## 5  ( 1 ) " "                     " "
## 6  ( 1 ) " "                     " "
## 7  ( 1 ) " "                     " "
## 8  ( 1 ) " "                     " "
##           room_type.Private.room room_type.Shared.room bed_type.Couch
## 1  ( 1 ) "*"                    " "                   " "
## 2  ( 1 ) "*"                    " "                   " "
## 3  ( 1 ) "*"                    "*"                   " "
## 4  ( 1 ) "*"                    "*"                   " "
## 5  ( 1 ) "*"                    "*"                   " "
## 6  ( 1 ) "*"                    "*"                   " "
## 7  ( 1 ) "*"                    "*"                   " "
## 8  ( 1 ) "*"                    " "                   " "
##           bed_type.Futon bed_type.Pull.out.Sofa bed_type.Real.Bed
## 1  ( 1 ) " "            " "                    " "
## 2  ( 1 ) " "            " "                    " "
## 3  ( 1 ) " "            " "                    " "
## 4  ( 1 ) " "            " "                    " "
## 5  ( 1 ) " "            " "                    " "
## 6  ( 1 ) " "            " "                    " "
## 7  ( 1 ) " "            " "                    " "
## 8  ( 1 ) " "            " "                    " "
##           cancellation_policy.moderate cancellation_policy.strict
## 1  ( 1 ) " "                          " "
## 2  ( 1 ) " "                          " "
## 3  ( 1 ) " "                          " "
## 4  ( 1 ) " "                          " "
## 5  ( 1 ) " "                          " "
## 6  ( 1 ) " "                          " "
## 7  ( 1 ) " "                          " "
## 8  ( 1 ) " "                          " "
##           cancellation_policy.super_strict_30
## 1  ( 1 ) " "
## 2  ( 1 ) " "
## 3  ( 1 ) " "
## 4  ( 1 ) " "
## 5  ( 1 ) " "
## 6  ( 1 ) " "
## 7  ( 1 ) " "
## 8  ( 1 ) " "
##           cancellation_policy.super_strict_60 neighborhood.Back.Bay
## 1  ( 1 ) " "                                 " "
## 2  ( 1 ) " "                                 " "
## 3  ( 1 ) " "                                 " "
## 4  ( 1 ) " "                                 "*"
```

```
## 5  ( 1 ) " "                                 "*"
## 6  ( 1 ) " "                                 "*"
## 7  ( 1 ) " "                                 "*"
## 8  ( 1 ) " "                                 "*"
##          neighborhood.Bay.Village neighborhood.Beacon.Hill
## 1  ( 1 ) " "                      " "
## 2  ( 1 ) " "                      " "
## 3  ( 1 ) " "                      " "
## 4  ( 1 ) " "                      " "
## 5  ( 1 ) " "                      " "
## 6  ( 1 ) " "                      " "
## 7  ( 1 ) " "                      "*"
## 8  ( 1 ) " "                      "*"
##          neighborhood.Brighton neighborhood.Charlestown
## 1  ( 1 ) " "                   " "
## 2  ( 1 ) " "                   " "
## 3  ( 1 ) " "                   " "
## 4  ( 1 ) " "                   " "
## 5  ( 1 ) " "                   " "
## 6  ( 1 ) " "                   " "
## 7  ( 1 ) " "                   " "
## 8  ( 1 ) " "                   " "
##          neighborhood.Chinatown neighborhood.Dorchester
## 1  ( 1 ) " "                    " "
## 2  ( 1 ) " "                    " "
## 3  ( 1 ) " "                    " "
## 4  ( 1 ) " "                    " "
## 5  ( 1 ) " "                    " "
## 6  ( 1 ) " "                    " "
## 7  ( 1 ) " "                    " "
## 8  ( 1 ) " "                    " "
##          neighborhood.Downtown neighborhood.East.Boston
## 1  ( 1 ) " "                   " "
## 2  ( 1 ) " "                   " "
## 3  ( 1 ) " "                   " "
## 4  ( 1 ) " "                   " "
## 5  ( 1 ) "*"                   " "
## 6  ( 1 ) "*"                   " "
## 7  ( 1 ) "*"                   " "
## 8  ( 1 ) "*"                   " "
##          neighborhood.Fenway neighborhood.Hyde.Park
## 1  ( 1 ) " "                 " "
## 2  ( 1 ) " "                 " "
## 3  ( 1 ) " "                 " "
## 4  ( 1 ) " "                 " "
## 5  ( 1 ) " "                 " "
## 6  ( 1 ) " "                 " "
## 7  ( 1 ) " "                 " "
## 8  ( 1 ) " "                 " "
##          neighborhood.Jamaica.Plain neighborhood.Leather.District
## 1  ( 1 ) " "                        " "
## 2  ( 1 ) " "                        " "
## 3  ( 1 ) " "                        " "
## 4  ( 1 ) " "                        " "
```

```
## 5  ( 1 ) " "                        " "
## 6  ( 1 ) " "                        " "
## 7  ( 1 ) " "                        " "
## 8  ( 1 ) " "                        " "
##          neighborhood.Longwood.Medical.Area neighborhood.Mattapan
## 1  ( 1 ) " "                                " "
## 2  ( 1 ) " "                                " "
## 3  ( 1 ) " "                                " "
## 4  ( 1 ) " "                                " "
## 5  ( 1 ) " "                                " "
## 6  ( 1 ) " "                                " "
## 7  ( 1 ) " "                                " "
## 8  ( 1 ) " "                                " "
##          neighborhood.Mission.Hill neighborhood.North.End
## 1  ( 1 ) " "                       " "
## 2  ( 1 ) " "                       " "
## 3  ( 1 ) " "                       " "
## 4  ( 1 ) " "                       " "
## 5  ( 1 ) " "                       " "
## 6  ( 1 ) " "                       " "
## 7  ( 1 ) " "                       " "
## 8  ( 1 ) " "                       " "
##          neighborhood.Roslindale neighborhood.Roxbury
## 1  ( 1 ) " "                     " "
## 2  ( 1 ) " "                     " "
## 3  ( 1 ) " "                     " "
## 4  ( 1 ) " "                     " "
## 5  ( 1 ) " "                     " "
## 6  ( 1 ) " "                     " "
## 7  ( 1 ) " "                     " "
## 8  ( 1 ) " "                     " "
##          neighborhood.South.Boston neighborhood.South.Boston.Waterfront
## 1  ( 1 ) " "                       " "
## 2  ( 1 ) " "                       " "
## 3  ( 1 ) " "                       " "
## 4  ( 1 ) " "                       " "
## 5  ( 1 ) " "                       " "
## 6  ( 1 ) " "                       " "
## 7  ( 1 ) " "                       " "
## 8  ( 1 ) " "                       "*"
##          neighborhood.South.End neighborhood.West.End
## 1  ( 1 ) " "                    " "
## 2  ( 1 ) " "                    " "
## 3  ( 1 ) " "                    " "
## 4  ( 1 ) " "                    " "
## 5  ( 1 ) " "                    " "
## 6  ( 1 ) "*"                    " "
## 7  ( 1 ) "*"                    " "
## 8  ( 1 ) "*"                    " "
##          neighborhood.West.Roxbury
## 1  ( 1 ) " "
## 2  ( 1 ) " "
## 3  ( 1 ) " "
## 4  ( 1 ) " "
```

```
## 5  ( 1 ) " "
## 6  ( 1 ) " "
## 7  ( 1 ) " "
## 8  ( 1 ) " "
```

```r
par(mfrow = c(2,2))
plot(reg.summary$rss, xlab = "Number of variables", ylab = "Residual Sum of Squares (RSS)", type = "l")
plot(reg.summary$adjr2, xlab = "Number of variables", ylab = "Adjacent R square", type = "l")
plot(reg.summary$cp, xlab = "Number of variables", ylab = "CP", type = "l")
plot(reg.summary$bic, xlab = "Number of variables", ylab = "BIC", type = "l")
```




```r
which.min(reg.summary$bic)
```

```
## [1] 8
```

TOP 8 predictors according to best subset are :

```r
# linear model based on 8 predictors
subset.model <- lm(price ~ room_type.Private.room + room_type.Shared.room + accommodates + bedrooms + i
# coefficients of the predictors
coef(regfit.full, 8)
```

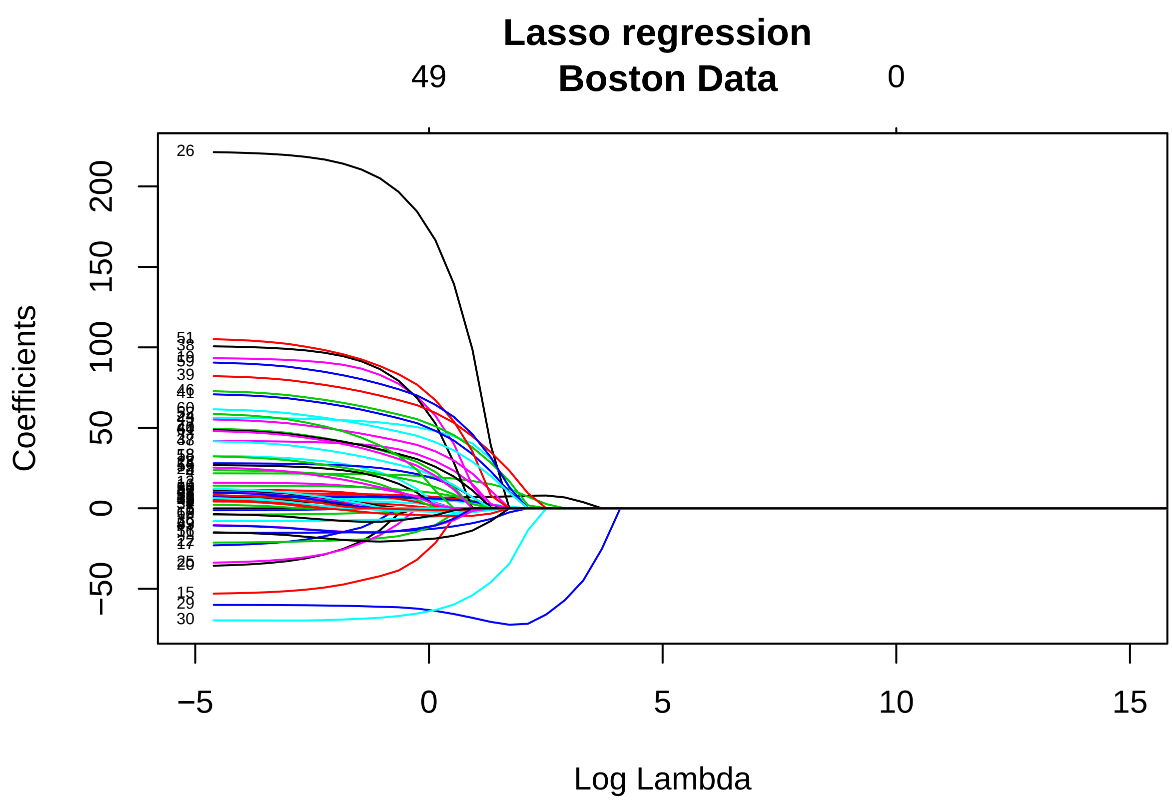
```
##                 (Intercept)              accommodates
##                  105.497182                  8.300836
##                    bedrooms    room_type.Private.room
##                   22.178145                -66.779191
##          neighborhood.Back.Bay   neighborhood.Beacon.Hill
##                   56.987277                 47.159364
```

```
##              neighborhood.Downtown neighborhood.South.Boston.Waterfront
##                          51.630679                            75.450650
##                neighborhood.South.End
##                          43.273643
```

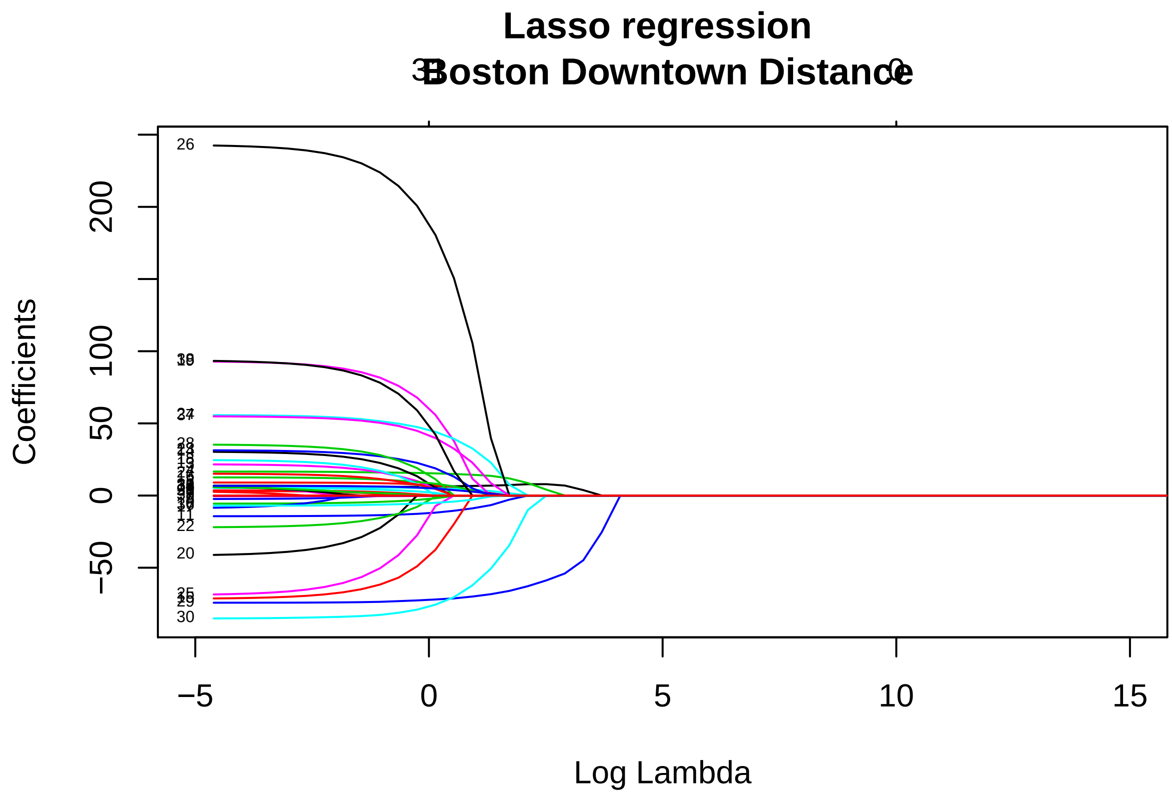
All predictors and Best subset were only used to understand our data better, now to implement linear regression we focus on two majoe approaches - lasso and ridge

Lasso Regression

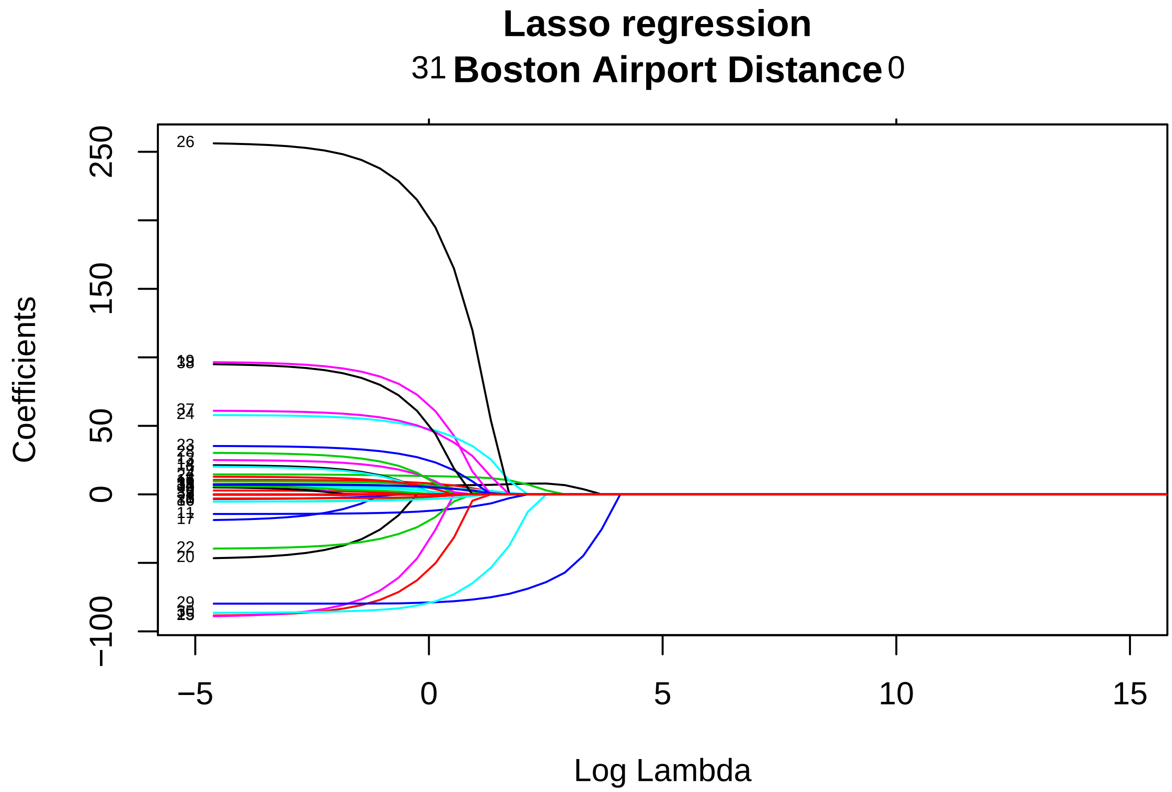
```
x.boston.data   <- model.matrix(price~.,boston.dummied.training)
x.boston.dboth  <- model.matrix(price~.,boston.dboth.dummied.training)
x.boston.ddowntown  <- model.matrix(price~.,boston.ddowntown.dummied.training)
x.boston.dairport   <- model.matrix(price~.,boston.dairport.dummied.training)

y.boston.data   <- boston.dummied.training$price
y.boston.dboth  <- boston.dboth.dummied.training$price
y.boston.ddowntown  <- boston.ddowntown.dummied.training$price
y.boston.dairport   <- boston.dairport.dummied.training$price

grid = 10^seq(15,-2, length = 100)
lasso.boston.data <- glmnet(x.boston.data,y.boston.data, alpha = 1, lambda = grid)
plot(lasso.boston.data, main = "Lasso regression \n Boston Data", label = TRUE, xvar = "lambda", xlim =
```



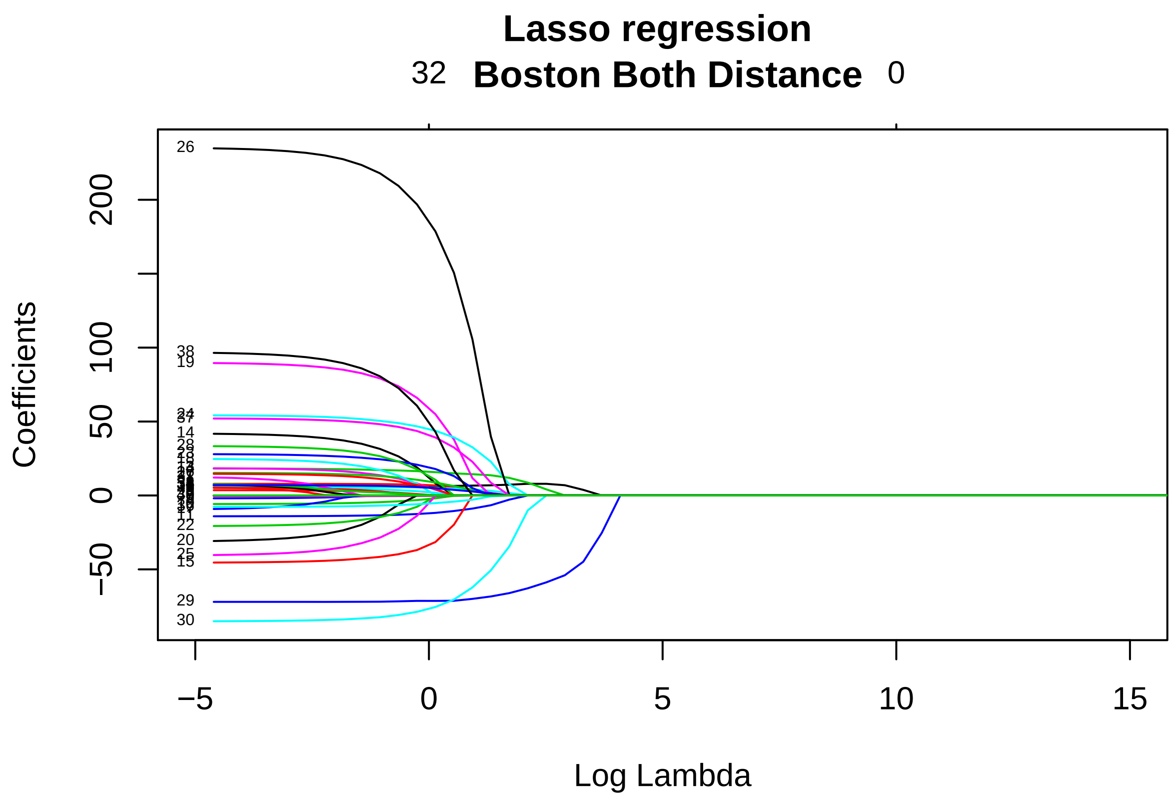

```
lasso.boston.ddowntown <- glmnet(x.boston.ddowntown,y.boston.ddowntown, alpha = 1, lambda = grid)
plot(lasso.boston.ddowntown, main = "Lasso regression \n Boston Downtown Distance", label = TRUE, xvar =
```



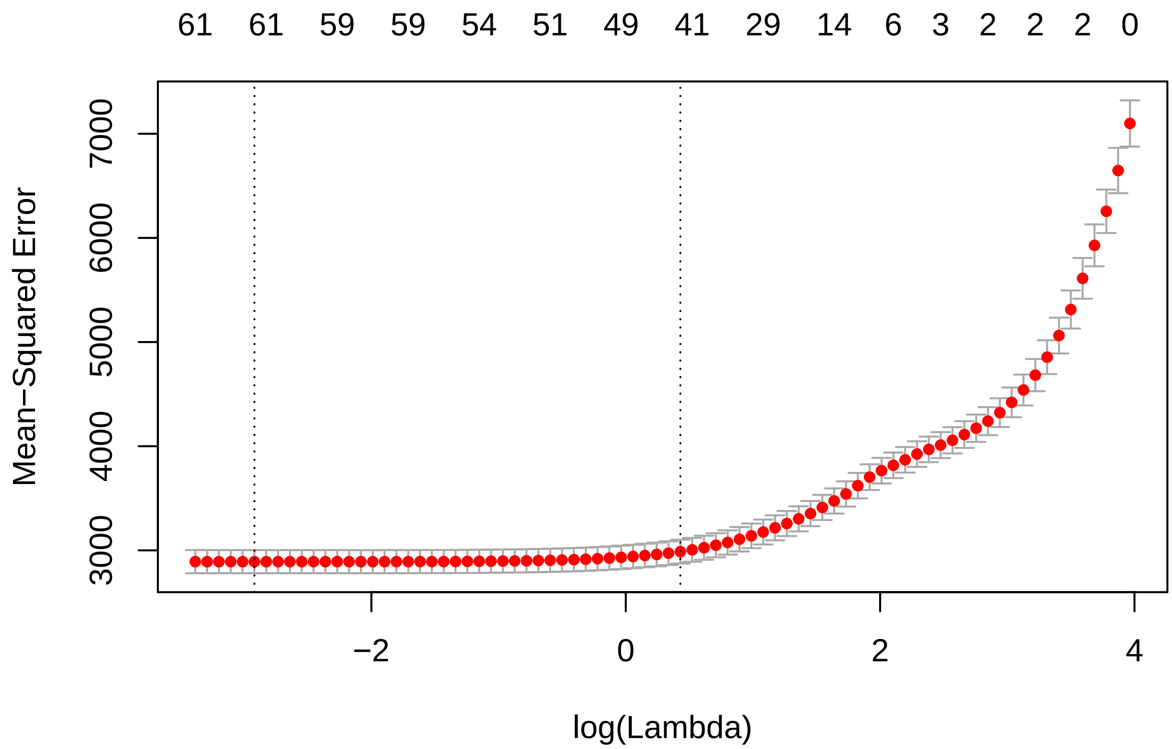

```
lasso.boston.dairport <- glmnet(x.boston.dairport,y.boston.dairport, alpha = 1, lambda = grid)
plot(lasso.boston.dairport, main = "Lasso regression \n Boston Airport Distance", label = TRUE, xvar =
```



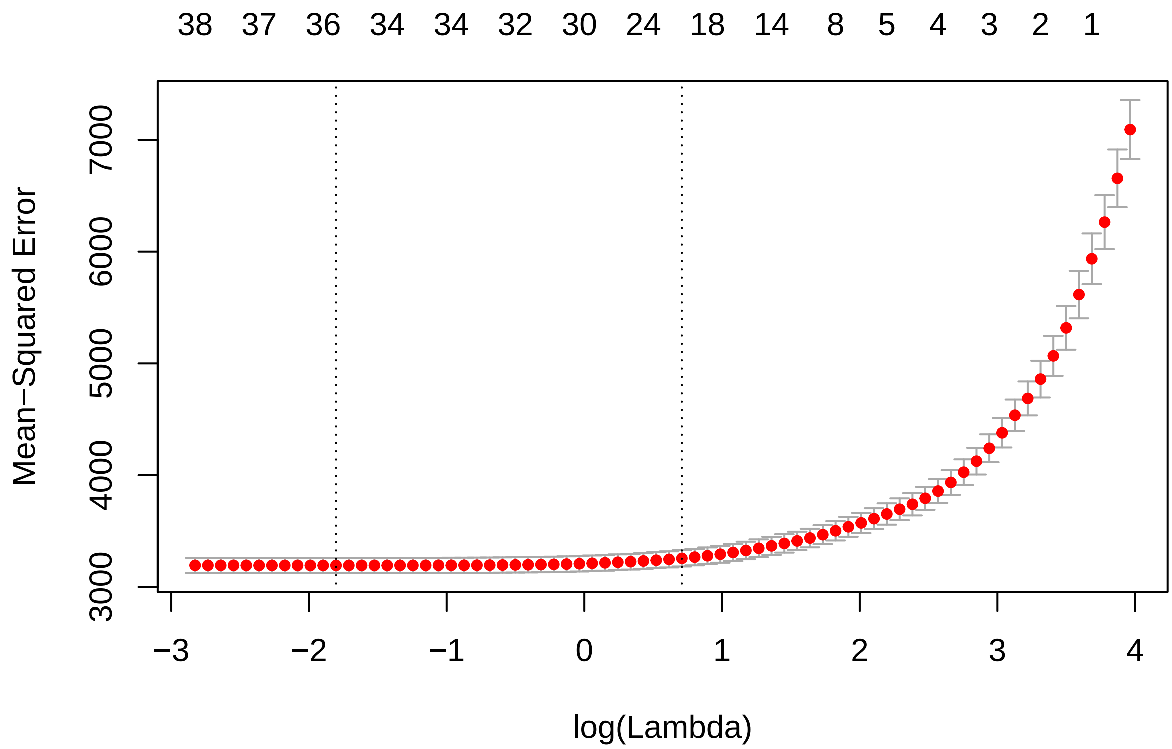

```
lasso.boston.dboth <- glmnet(x.boston.dboth,y.boston.dboth, alpha = 1, lambda = grid)
plot(lasso.boston.dboth, main = "Lasso regression \n Boston Both Distance", label = TRUE, xvar = "lambda
```



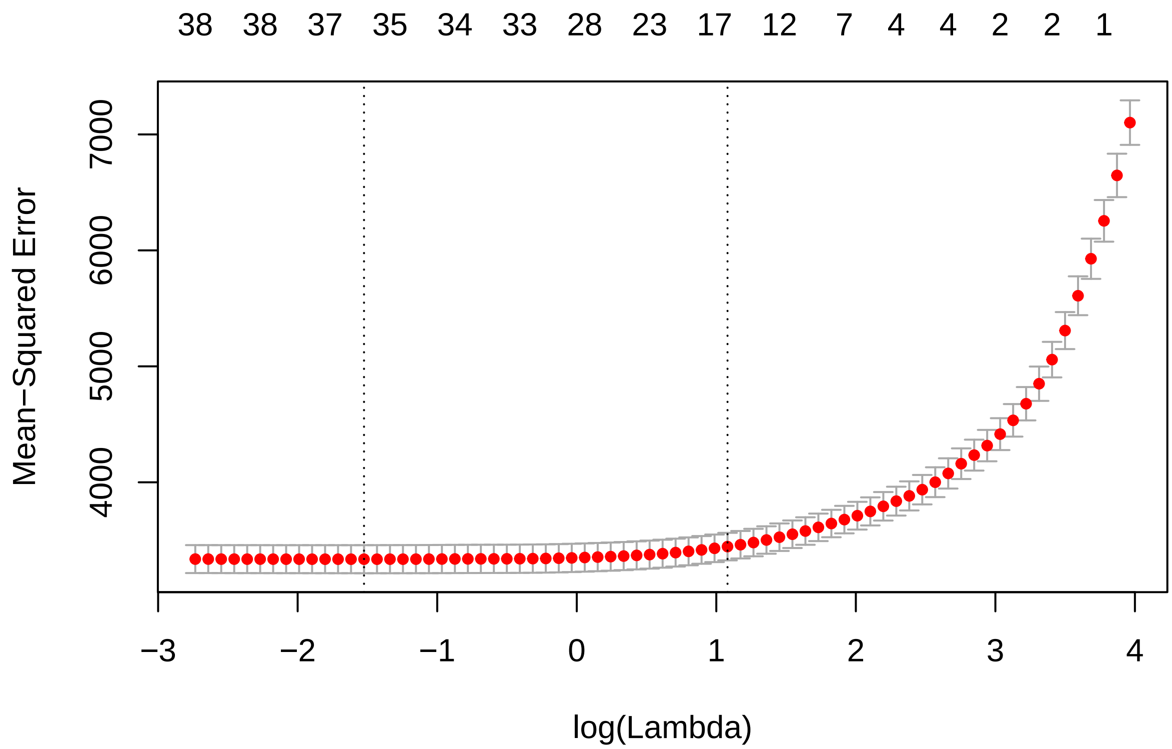

```
cv.out.data <- cv.glmnet(x.boston.data,y.boston.data,alpha = 1)
plot(cv.out.data)
```



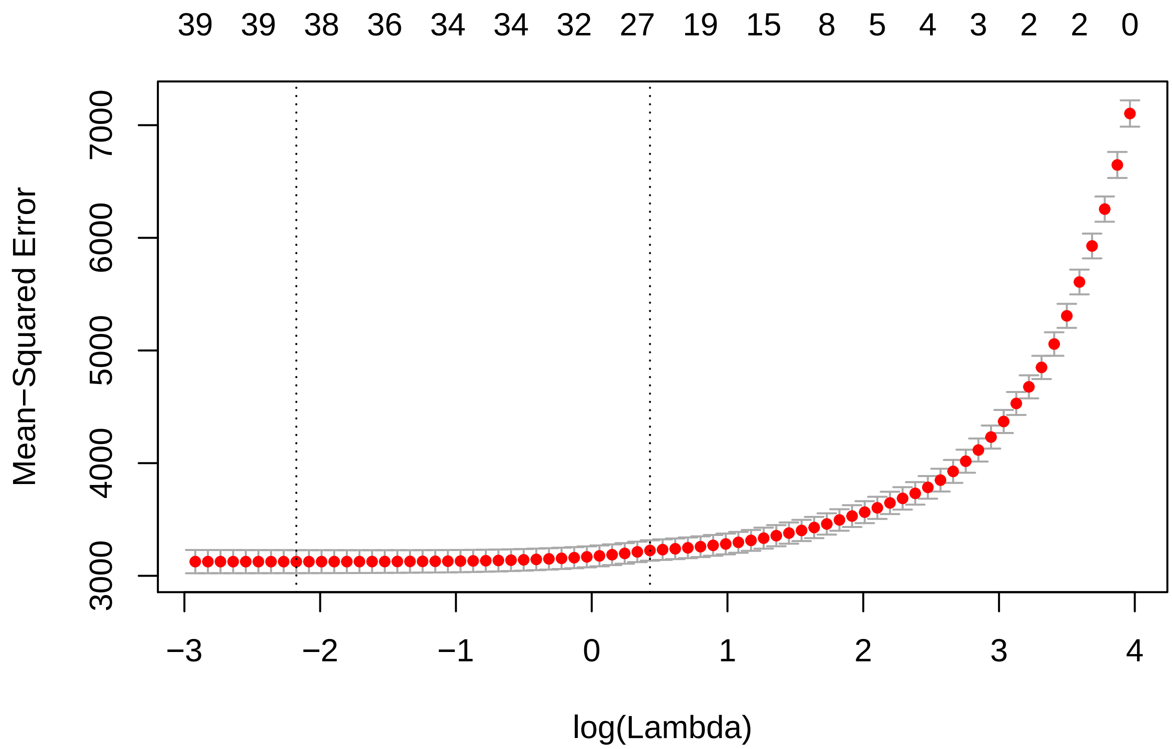

```
cv.out.ddowntown <- cv.glmnet(x.boston.ddowntown,y.boston.ddowntown,alpha = 1)
plot(cv.out.ddowntown)
```




```
cv.out.dairport <- cv.glmnet(x.boston.dairport,y.boston.dairport,alpha = 1)
plot(cv.out.dairport)
```




```
cv.out.dboth <- cv.glmnet(x.boston.dboth,y.boston.dboth,alpha = 1)
plot(cv.out.dboth)
```




```r
bestlam.lasso.data <- cv.out.data$lambda.min
cat("Best lambda Boston Data" , bestlam.lasso.data, "\n")
```

```
## Best lambda Boston Data 0.05393749
```

```r
cat("Best log lambda Boston Data", log(bestlam.lasso.data), "\n")
```

```
## Best log lambda Boston Data -2.91993
```

```r
bestlam.lasso.ddowntown <- cv.out.ddowntown$lambda.min
cat("Best lambda Boston Downtown" , bestlam.lasso.ddowntown, "\n")
```

```
## Best lambda Boston Downtown 0.1647173
```

```r
cat("Best log lambda Boston Downtown" , log(bestlam.lasso.ddowntown), "\n")
```

```
## Best log lambda Boston Downtown -1.803525
```

```r
bestlam.lasso.dairport <- cv.out.dairport$lambda.min
cat("Best lambda Boston Airport" , bestlam.lasso.dairport, "\n")
```

```
## Best lambda Boston Airport 0.2177466
```

```r
cat("Best log lambda Boston Airport" , log(bestlam.lasso.dairport), "\n")
```

```
## Best log lambda Boston Airport -1.524423
```

```r
bestlam.lasso.dboth <- cv.out.dboth$lambda.min
cat("Best lambda Boston Both" , bestlam.lasso.dboth, "\n")
```

```
## Best lambda Boston Both 0.1135332
```

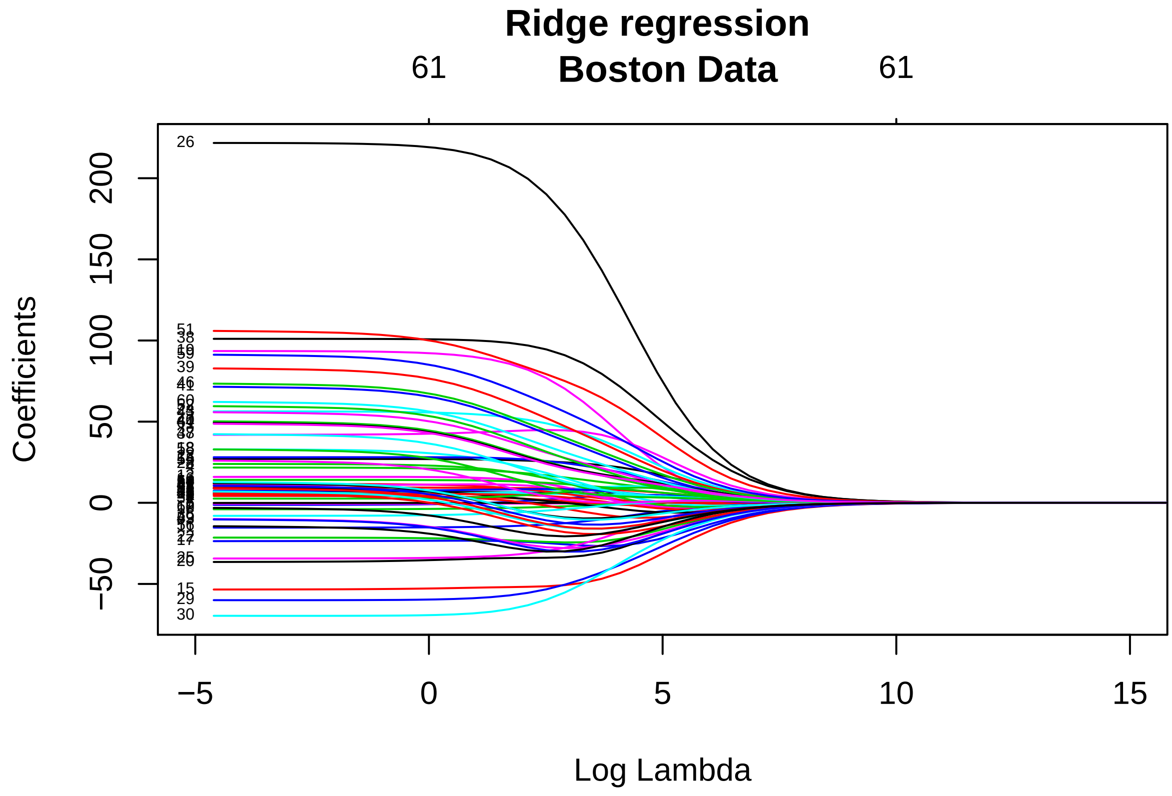
```
cat("Best log lambda Boston Both" , log(bestlam.lasso.dboth), "\n")
```

```
## Best log lambda Boston Both -2.17566
```

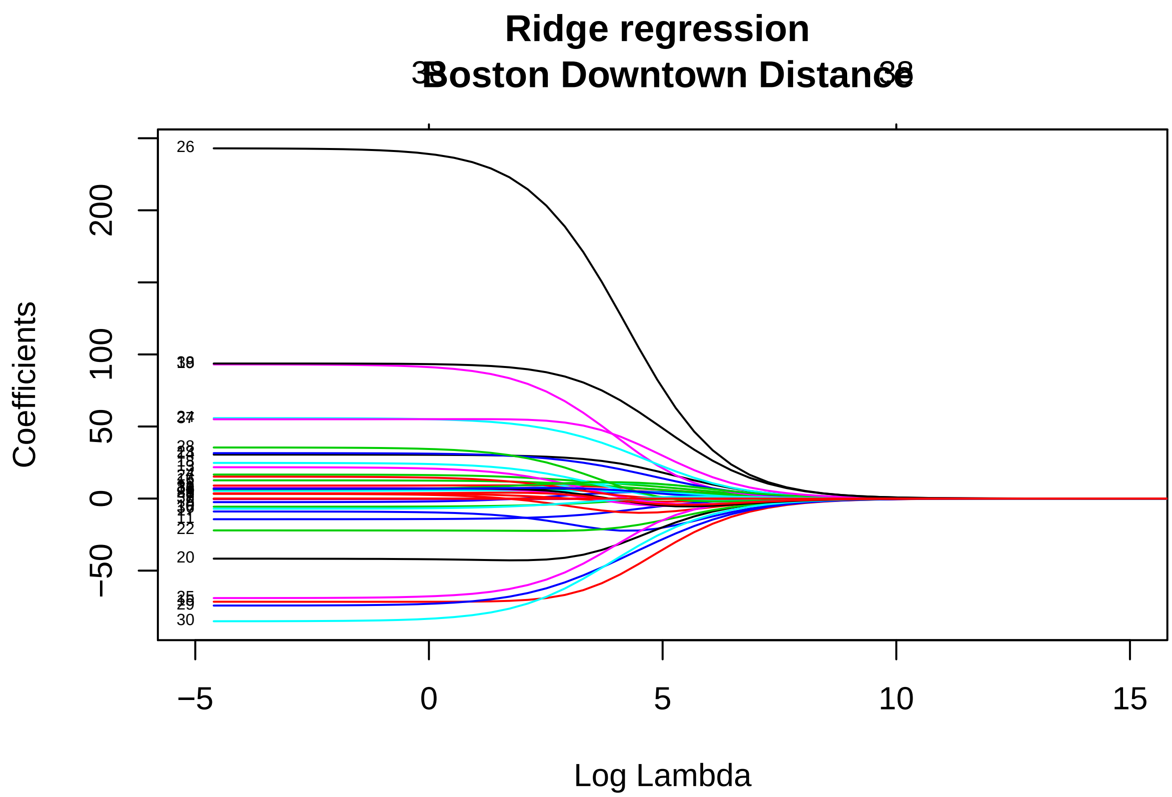
```
lasso.model.data <- glmnet(x.boston.data, y.boston.data, alpha=1, lambda = bestlam.lasso.data)
lasso.model.ddowntown <- glmnet(x.boston.ddowntown, y.boston.ddowntown, alpha=1, lambda = bestlam.lasso
lasso.model.dairport <- glmnet(x.boston.dairport, y.boston.dairport, alpha=1, lambda = bestlam.lasso.da
lasso.model.dboth <- glmnet(x.boston.dboth, y.boston.dboth, alpha=1, lambda = bestlam.lasso.dboth)
```

Ridge Regression

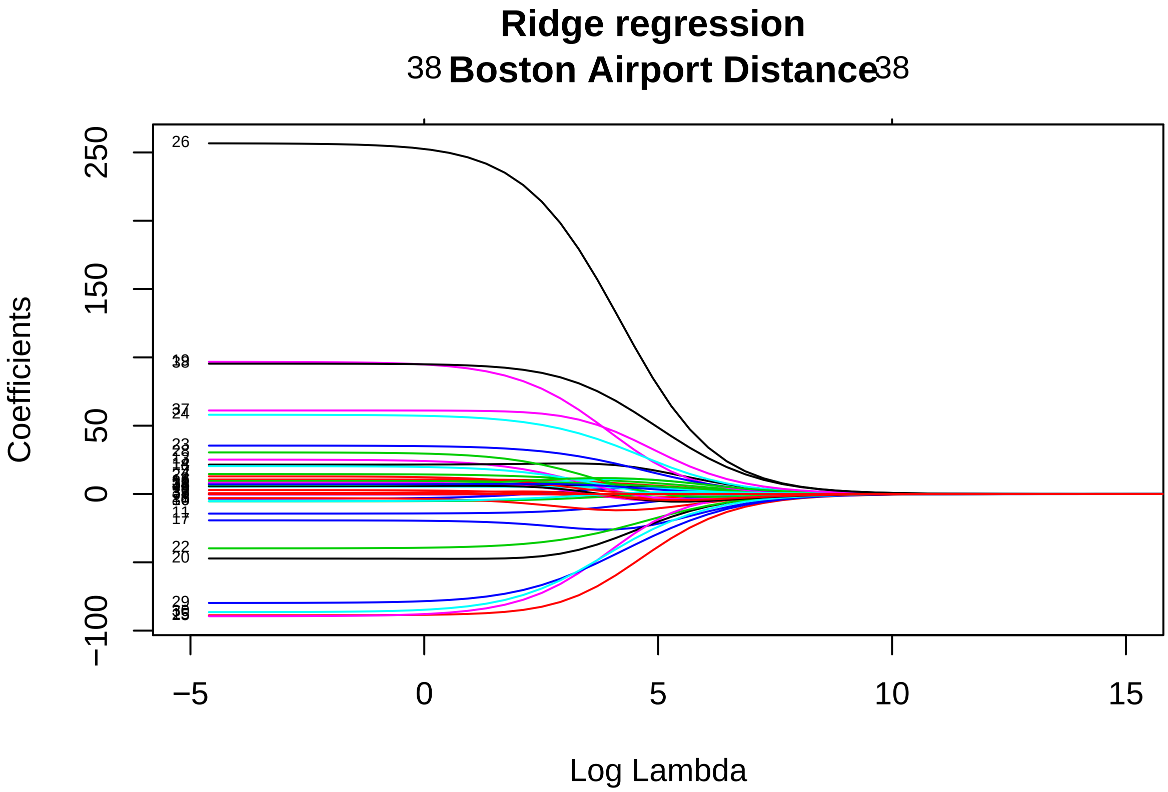
```
grid = 10^seq(15,-2, length = 100)
ridge.boston.data <- glmnet(x.boston.data,y.boston.data, alpha = 0, lambda = grid)
plot(ridge.boston.data, main = "Ridge regression \n Boston Data", label = TRUE, xvar = "lambda", xlim =
```



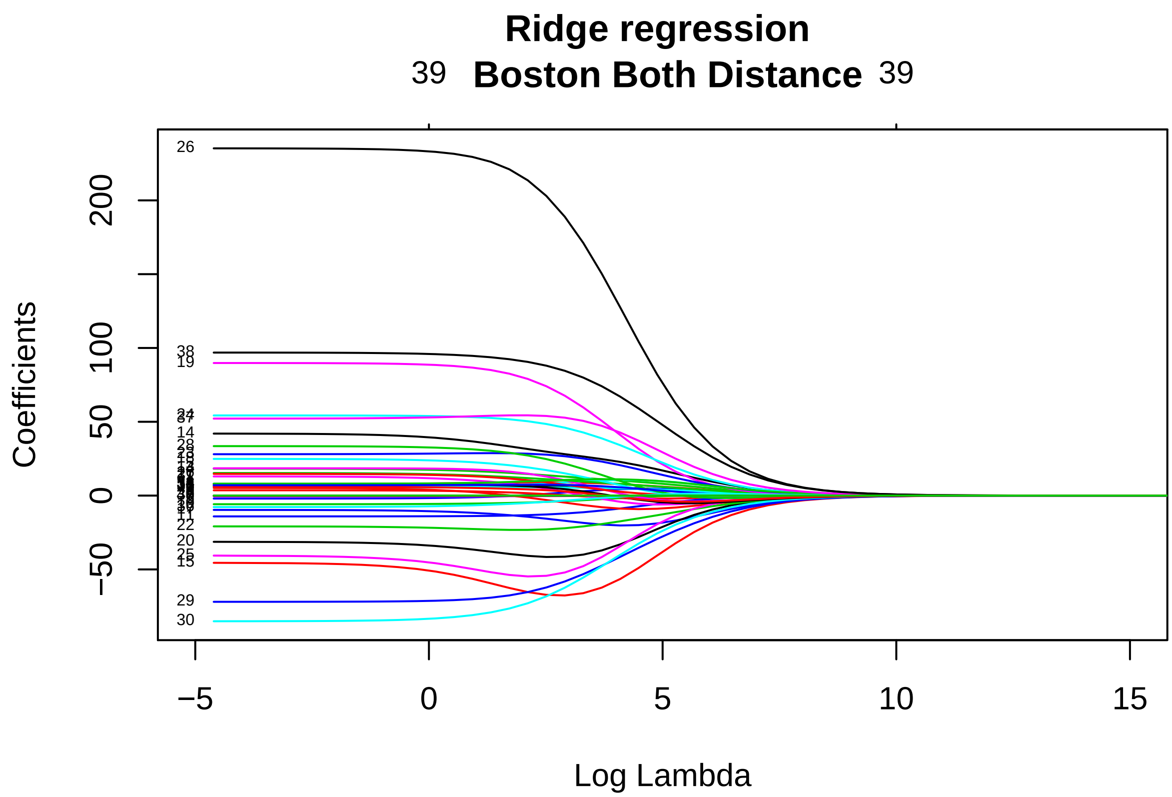

```
ridge.boston.ddowntown <- glmnet(x.boston.ddowntown,y.boston.ddowntown, alpha = 0, lambda = grid)
plot(ridge.boston.ddowntown, main = "Ridge regression \n Boston Downtown Distance", label = TRUE, xvar =
```



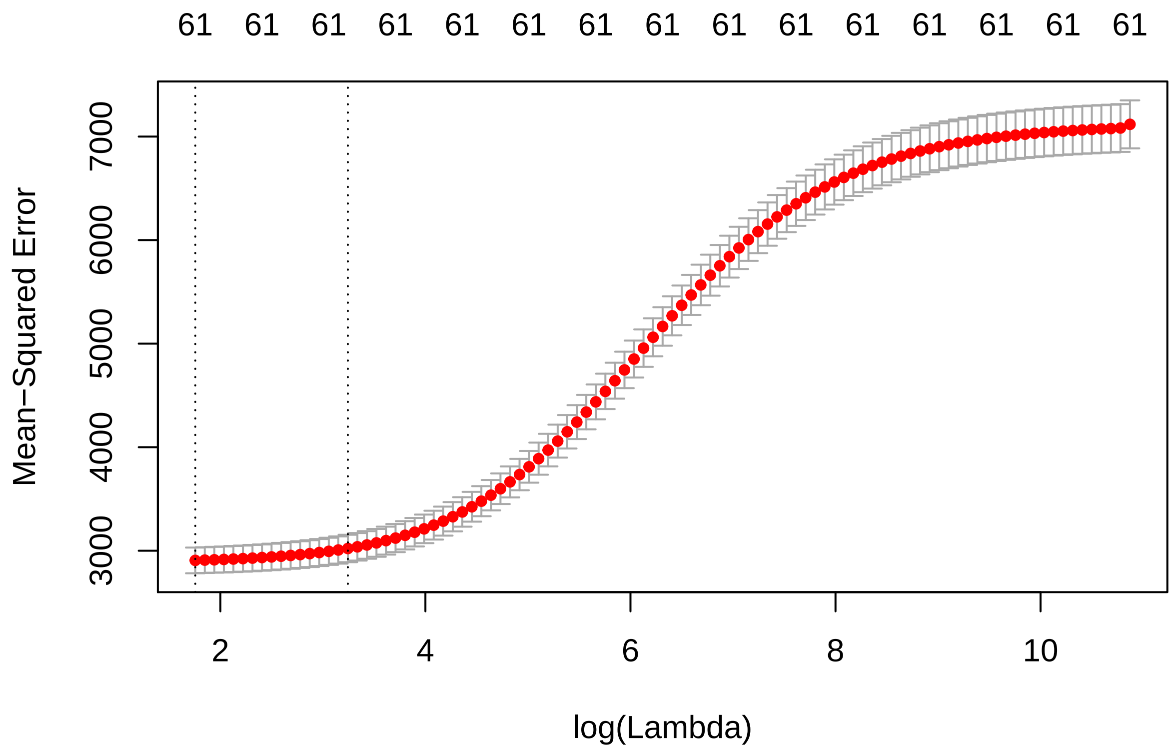

```
ridge.boston.dairport <- glmnet(x.boston.dairport,y.boston.dairport, alpha = 0, lambda = grid)
plot(ridge.boston.dairport, main = "Ridge regression \n Boston Airport Distance", label = TRUE, xvar =
```



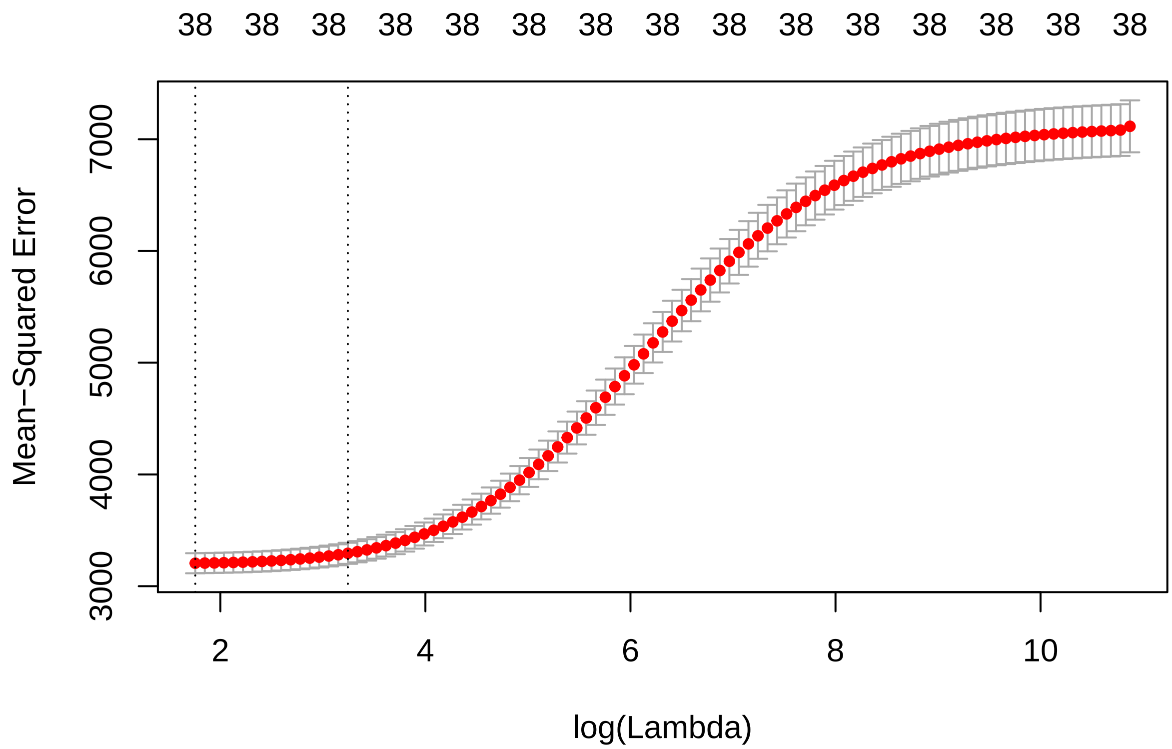

```
ridge.boston.dboth <- glmnet(x.boston.dboth,y.boston.dboth, alpha = 0, lambda = grid)
plot(ridge.boston.dboth, main = "Ridge regression \n Boston Both Distance", label = TRUE, xvar = "lambda
```



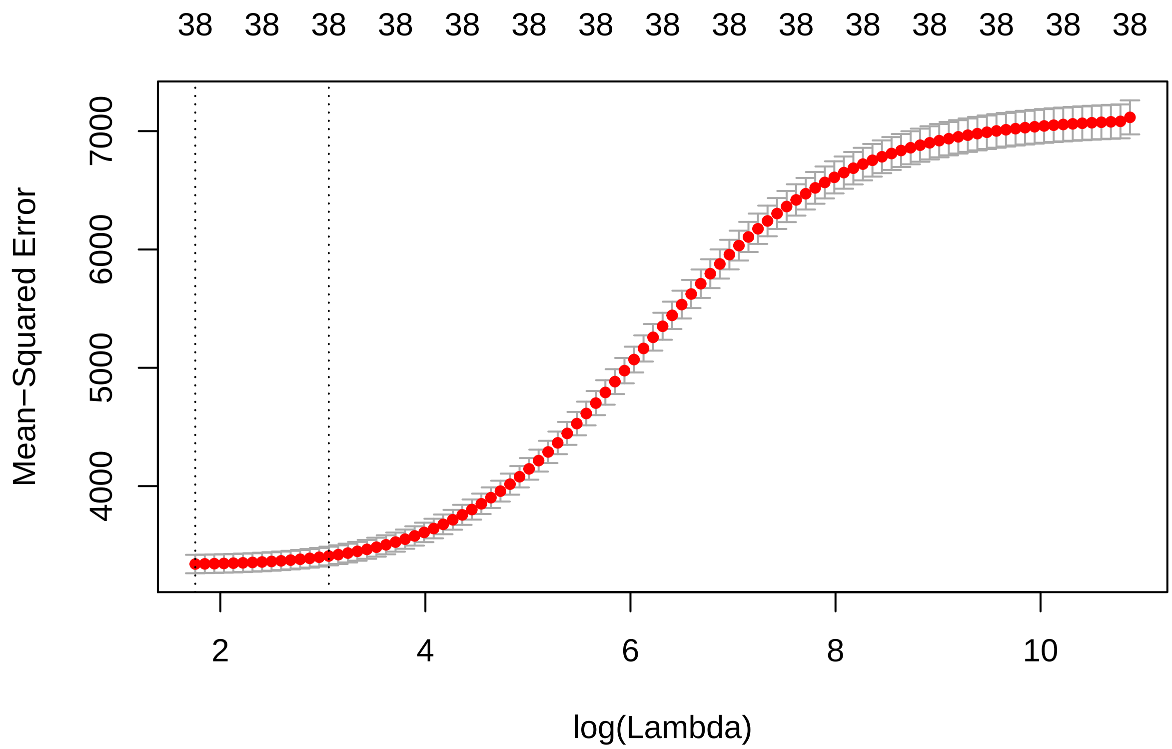

```r
cv.out.data <- cv.glmnet(x.boston.data,y.boston.data,alpha = 0)
plot(cv.out.data)
```



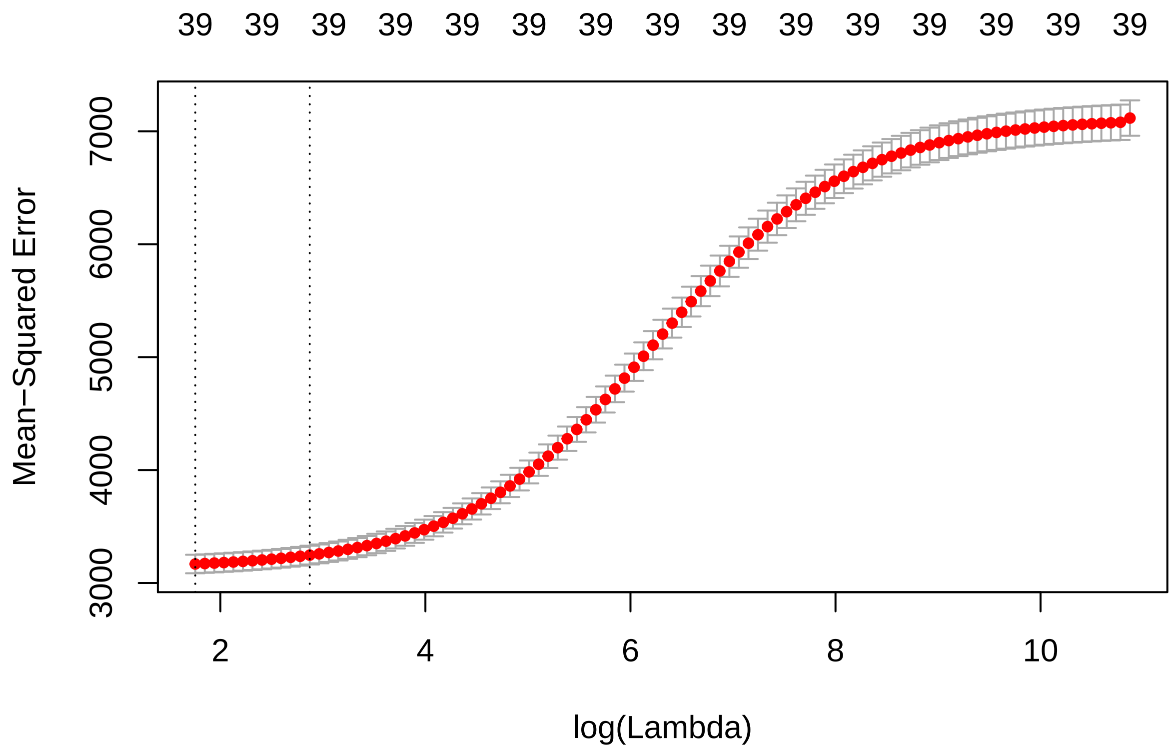

```
cv.out.ddowntown <- cv.glmnet(x.boston.ddowntown,y.boston.ddowntown,alpha = 0)
plot(cv.out.ddowntown)
```




```r
cv.out.dairport <- cv.glmnet(x.boston.dairport,y.boston.dairport,alpha = 0)
plot(cv.out.dairport)
```




```
cv.out.dboth <- cv.glmnet(x.boston.dboth,y.boston.dboth,alpha = 0)
plot(cv.out.dboth)
```




```r
bestlam.ridge.data <- cv.out.data$lambda.min
cat("Best lambda Boston Data" , bestlam.ridge.data, "\n")
```

```
## Best lambda Boston Data 5.78354
```

```r
cat("Best log lambda Boston Data", log(bestlam.ridge.data), "\n")
```

```
## Best log lambda Boston Data 1.755016
```

```r
bestlam.ridge.ddowntown <- cv.out.ddowntown$lambda.min
cat("Best lambda Boston Downtown" , bestlam.ridge.ddowntown, "\n")
```

```
## Best lambda Boston Downtown 5.78354
```

```r
cat("Best log lambda Boston Downtown" , log(bestlam.ridge.ddowntown), "\n")
```

```
## Best log lambda Boston Downtown 1.755016
```

```r
bestlam.ridge.dairport <- cv.out.dairport$lambda.min
cat("Best lambda Boston Airport" , bestlam.ridge.dairport, "\n")
```

```
## Best lambda Boston Airport 5.78354
```

```r
cat("Best log lambda Boston Airport" , log(bestlam.ridge.dairport), "\n")
```

```
## Best log lambda Boston Airport 1.755016
```

```r
bestlam.ridge.dboth <- cv.out.dboth$lambda.min
cat("Best lambda Boston Both" , bestlam.ridge.dboth, "\n")
```

```
## Best lambda Boston Both 5.78354
```

```r
cat("Best log lambda Boston Both" , log(bestlam.ridge.dboth), "\n")
```

```
## Best log lambda Boston Both 1.755016
```

```r
ridge.model.data <- glmnet(x.boston.data, y.boston.data, alpha=1, lambda = bestlam.ridge.data)
ridge.model.ddowntown <- glmnet(x.boston.ddowntown, y.boston.ddowntown, alpha=1, lambda = bestlam.ridge
ridge.model.dairport <- glmnet(x.boston.dairport, y.boston.dairport, alpha=1, lambda = bestlam.ridge.da
ridge.model.dboth <- glmnet(x.boston.dboth, y.boston.dboth, alpha=1, lambda = bestlam.ridge.dboth)
```

```r
rmse <- function(test_data, model) {
  return(sqrt(mean((test_data$price - predict(model, newx = model.matrix(price~.,test_data)))^ 2)))
}

print("LASSO")
```

```
## [1] "LASSO"
```

```r
cat("RMSE for Boston Data using Lasso", rmse(boston.dummied.model_selection, lasso.model.data), "$\n")
```

```
## RMSE for Boston Data using Lasso 56.25078 $
```

```r
cat("RMSE for Boston Downtown Data using Lasso", rmse(boston.ddowntown.dummied.model_selection, lasso.mo
```

```
## RMSE for Boston Downtown Data using Lasso 59.17001 $
```

```r
cat("RMSE for Boston Airport Data using Lasso", rmse(boston.dairport.dummied.model_selection, lasso.mode
```

```
## RMSE for Boston Airport Data using Lasso 60.42277 $
```

```r
cat("RMSE for Boston Both Data using Lasso", rmse(boston.dboth.dummied.model_selection, lasso.model.dbo
```

```
## RMSE for Boston Both Data using Lasso 58.62441 $
```

```r
print("RIDGE")
```

```
## [1] "RIDGE"
```

```r
cat("RMSE for Boston Data using Ridge", rmse(boston.dummied.model_selection, ridge.model.data), "$\n")
```

```
## RMSE for Boston Data using Ridge 62.27309 $
```

```r
cat("RMSE for Boston Downtown Data using Ridge", rmse(boston.ddowntown.dummied.model_selection, ridge.mo
```

```
## RMSE for Boston Downtown Data using Ridge 61.98493 $
```

```r
cat("RMSE for Boston Airport Data using Ridge", rmse(boston.dairport.dummied.model_selection, ridge.mode
```

```
## RMSE for Boston Airport Data using Ridge 63.11274 $
```

```r
cat("RMSE for Boston Both Data using Ridge", rmse(boston.dboth.dummied.model_selection, ridge.model.dbo
```

```
## RMSE for Boston Both Data using Ridge 61.98493 $
```

```r
cat("RMSE for Boston Data using Lasso - Validation Set 1", rmse(boston.dummied.validation_1, lasso.mode
```

```
## RMSE for Boston Data using Lasso - Validation Set 1 56.81055 $
```

```r
cat("RMSE for Boston Downtown Data using Lasso - Validation Set 1", rmse(boston.ddowntown.dummied.valid
```

```
## RMSE for Boston Downtown Data using Lasso - Validation Set 1 58.98283 $
```

```r
cat("RMSE for Boston Airport Data using Lasso - Validation Set 1", rmse(boston.dairport.dummied.validat
```

```
## RMSE for Boston Airport Data using Lasso - Validation Set 1 60.7616 $
```

```r
cat("RMSE for Boston Both Data using Lasso - Validation Set 1", rmse(boston.dboth.dummied.validation_1,
```

```
## RMSE for Boston Both Data using Lasso - Validation Set 1 58.15547 $
```

```r
a = predict(lasso.model.data, s = bestlam.lasso.data, type = "coefficients")
cat("Predictors for Lasso Boston Data", nrow(a), "\n")
```

```
## Predictors for Lasso Boston Data 63
```

```r
a = predict(lasso.model.ddowntown, s = bestlam.lasso.ddowntown, type = "coefficients")
cat("Predictors for Lasso Boston Donwtown", nrow(a), "\n")
```

```
## Predictors for Lasso Boston Donwtown 40
```

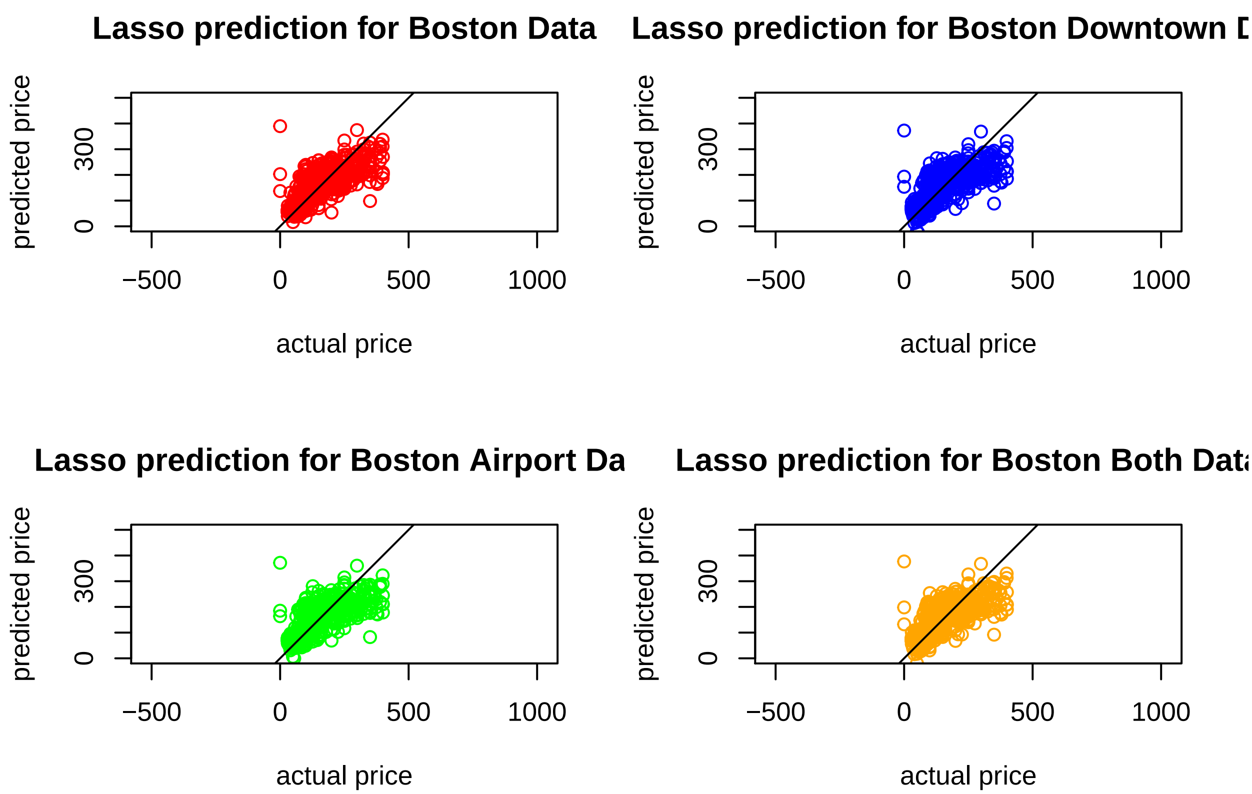
```r
a = predict(lasso.model.dairport, s = bestlam.lasso.dairport, type = "coefficients")
cat("Predictors for Lasso Boston Airport", nrow(a), "\n")
```

```
## Predictors for Lasso Boston Airport 40
```

```r
a = predict(lasso.model.dboth, s = bestlam.lasso.dboth, type = "coefficients")
cat("Predictors for Lasso Boston Both", nrow(a), "\n")
```

```
## Predictors for Lasso Boston Both 41
```

```r
plot_predicts <-function(predicted_price, real_price, text, color){
  plot(x = real_price, y = predict_price, xlab = "actual price",
  ylab = "predicted price", main = text,xlim= c(0,500), ylim= c(0,500), col = color, asp=1)
  abline(a = 0, b = 1)
}
par(mfrow=c(2,2))
predict_price = predict(lasso.model.data, newx = model.matrix(price~.,boston.dummied.model_selection))
real_price = boston.dummied.model_selection$price
plot_predicts(predict_price, real_price, "Lasso prediction for Boston Data", "red")

predict_price = predict(lasso.model.ddowntown, newx = model.matrix(price~.,boston.ddowntown.dummied.mode
real_price = boston.dummied.model_selection$price
plot_predicts(predict_price, real_price, "Lasso prediction for Boston Downtown Data", "blue")

predict_price = predict(lasso.model.dairport, newx = model.matrix(price~.,boston.dairport.dummied.model_
real_price = boston.dummied.model_selection$price
plot_predicts(predict_price, real_price, "Lasso prediction for Boston Airport Data", "green")


predict_price = predict(lasso.model.dboth, newx = model.matrix(price~.,boston.dboth.dummied.model_selec
real_price = boston.dummied.model_selection$price
plot_predicts(predict_price, real_price, "Lasso prediction for Boston Both Data", "orange")
```



GAM

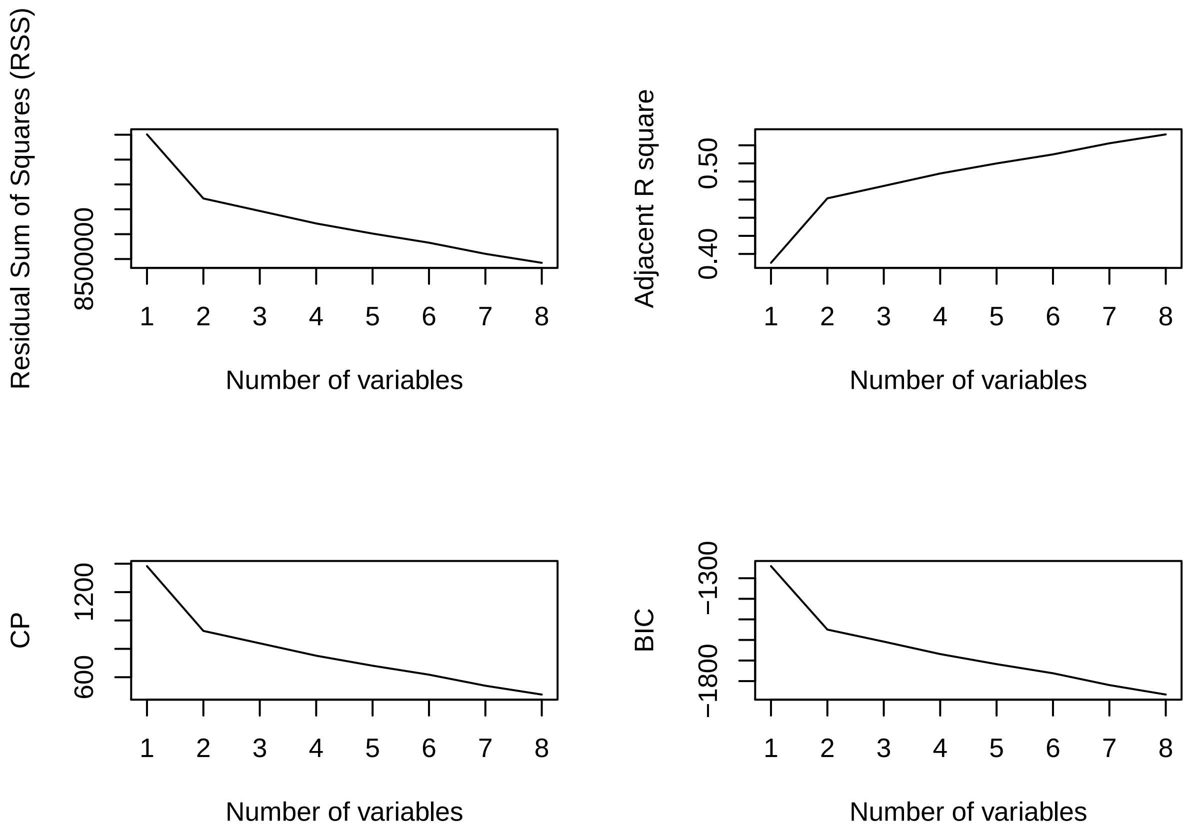
```
# Helper function

## @param test_data: data frame representing the test dataset
## @param model: GAM to be evaluated
## @returns: the root mean square error of the given GAM's predictions
rmse <- function(test_data, model) {
  return(sqrt(mean((test_data$price - predict.gam(model, test_data)) ^ 2)))
}

plot_predicts_gam <-function(test_data, model, text, color){
  real_price = test_data$price
  predict_price = predict.gam(model, test_data)
  plot(x = real_price, y = predict_price, xlab = "actual price",
  ylab = "predicted price", main = text,xlim= c(0,500), ylim= c(0,500), col= color, asp=1)
  abline(a = 0, b = 1)
}
```

Variable selection methods

Exploring three variable selection methods on the original dataset.

Regression subset selction

```r
reg1 <- regsubsets(price~., data = boston.data.training, really.big = T)
reg1.summary <- summary(reg1)

par(mfrow = c(2,2))
plot(reg1.summary$rss, xlab = "Number of variables", ylab = "Residual Sum of Squares (RSS)", type = "l"
plot(reg1.summary$adjr2, xlab = "Number of variables", ylab = "Adjacent R square", type = "l")
plot(reg1.summary$cp, xlab = "Number of variables", ylab = "CP", type = "l")
plot(reg1.summary$bic, xlab = "Number of variables", ylab = "BIC", type = "l")
```




```r
which.min(reg1.summary$bic)
```

```
## [1] 8
```

```r
# Results: neighborhood, room_type, bedrooms
```

```r
# GAM based on the above predictors
gam.var1 <- gam(price ~ neighborhood + room_type +s(bedrooms, k=5, bs="cr"), data=boston.data.training,
summary(gam.var1)
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## price ~ neighborhood + room_type + s(bedrooms, k = 5, bs = "cr")
```

```
##
## Parametric coefficients:
##                                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)                       141.9999     4.7695  29.772  < 2e-16
## neighborhoodBack Bay               77.4922     6.1283  12.645  < 2e-16
## neighborhoodBay Village            58.8643    15.5698   3.781  0.00016
## neighborhoodBeacon Hill            66.5157     6.5376  10.174  < 2e-16
## neighborhoodBrighton                6.7294     6.1968   1.086  0.27761
## neighborhoodCharlestown            56.6379     8.1568   6.944 4.85e-12
## neighborhoodChinatown              53.9698     8.4620   6.378 2.13e-10
## neighborhoodDorchester              5.5711     5.9301   0.939  0.34758
## neighborhoodDowntown               73.7092     6.5780  11.205  < 2e-16
## neighborhoodEast Boston             8.4492     6.3624   1.328  0.18430
## neighborhoodFenway                 41.7047     6.1351   6.798 1.32e-11
## neighborhoodHyde Park              -8.9881    11.9928  -0.749  0.45365
## neighborhoodJamaica Plain          14.3229     5.7816   2.477  0.01330
## neighborhoodLeather District      119.0248    28.2959   4.206 2.69e-05
## neighborhoodLongwood Medical Area  55.9726    28.2588   1.981  0.04773
## neighborhoodMattapan               -5.3499    13.8659  -0.386  0.69966
## neighborhoodMission Hill           11.0646     7.8554   1.409  0.15910
## neighborhoodNorth End              19.0931     7.4269   2.571  0.01020
## neighborhoodRoslindale             -8.2625     8.4977  -0.972  0.33098
## neighborhoodRoxbury                 7.6340     6.6357   1.150  0.25007
## neighborhoodSouth Boston           36.7689     6.5236   5.636 1.93e-08
## neighborhoodSouth Boston Waterfront  93.1898    10.6667   8.737  < 2e-16
## neighborhoodSouth End              61.9936     6.1380  10.100  < 2e-16
## neighborhoodWest End               54.4899    11.5385   4.722 2.46e-06
## neighborhoodWest Roxbury            0.1855    10.0652   0.018  0.98530
## room_typePrivate room             -64.6402     2.9962 -21.574  < 2e-16
## room_typeShared room              -75.5122    10.1753  -7.421 1.58e-13
##
## (Intercept)                       ***
## neighborhoodBack Bay              ***
## neighborhoodBay Village           ***
## neighborhoodBeacon Hill           ***
## neighborhoodBrighton
## neighborhoodCharlestown           ***
## neighborhoodChinatown             ***
## neighborhoodDorchester
## neighborhoodDowntown              ***
## neighborhoodEast Boston
## neighborhoodFenway                ***
## neighborhoodHyde Park
## neighborhoodJamaica Plain         *
## neighborhoodLeather District      ***
## neighborhoodLongwood Medical Area *
## neighborhoodMattapan
## neighborhoodMission Hill
## neighborhoodNorth End             *
## neighborhoodRoslindale
## neighborhoodRoxbury
## neighborhoodSouth Boston          ***
## neighborhoodSouth Boston Waterfront ***
## neighborhoodSouth End             ***
```

```
## neighborhoodWest End                ***
## neighborhoodWest Roxbury
## room_typePrivate room               ***
## room_typeShared room                ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                edf Ref.df     F p-value
## s(bedrooms) 3.447  3.795 150.1  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.563   Deviance explained = 56.8%
## -REML =  13723  Scale est. = 3110.5    n = 2539
```

```
# R^2: 0.563

gam.var1.rmse <- rmse(boston.data.model_selection, gam.var1)
gam.var1.rmse # 57.4993
```

```
## [1] 57.4993
```

Forward Selection

```
null <- lm(price~1, data=boston.data.training)
full <- lm(price~., data=boston.data.training)

forward_selection <- step(null, scope=list(lower=null, upper=full), direction="forward")
```

```
## Start:  AIC=22521.81
## price ~ 1
##
##                            Df Sum of Sq      RSS   AIC
## + room_type                 2   7477354 10580368 21169
## + accommodates              1   5243844 12813878 21653
## + neighborhood             24   4619557 13438165 21820
## + beds                      1   3155623 14902099 22036
## + bedrooms                  1   2992742 15064980 22064
## + guests_included           1   1557511 16500211 22295
## + is_business_travel_ready  1   1148253 16909469 22357
## + property_type            16   1199234 16858488 22379
## + cancellation_policy       4    630948 17426775 22440
## + bathrooms                 1    570100 17487622 22442
## + X                         1    200775 17856948 22495
## + bed_type                  4    216139 17841584 22499
## + number_of_reviews         1     62511 17995211 22515
## + instant_bookable          1     60881 17996841 22515
## + host_is_superhost         1     42853 18014869 22518
## <none>                                  18057722 22522
## + host_identity_verified    1     13545 18044177 22522
## + minimum_nights            1      1741 18055981 22524
##
## Step:  AIC=21168.53
```

```
## price ~ room_type
##
##                           Df Sum of Sq      RSS   AIC
## + accommodates             1   1113390  9466978 20888
## + bedrooms                 1   1098259  9482108 20892
## + neighborhood            24    981822  9598546 20969
## + beds                     1    744614  9835754 20985
## + bathrooms                1    427798 10152570 21066
## + guests_included          1    390851 10189517 21075
## + property_type           16    366792 10213576 21111
## + cancellation_policy      4    117898 10462470 21148
## + instant_bookable         1     79146 10501222 21152
## + number_of_reviews        1     39960 10540408 21161
## + minimum_nights           1     38454 10541914 21161
## + is_business_travel_ready  1     23840 10556528 21165
## <none>                                 10580368 21169
## + X                        1      6263 10574105 21169
## + host_is_superhost        1      1748 10578620 21170
## + host_identity_verified   1       482 10579886 21170
## + bed_type                 4     12712 10567656 21174
##
## Step:  AIC=20888.21
## price ~ room_type + accommodates
##
##                           Df Sum of Sq     RSS   AIC
## + neighborhood            24   1434186 8032792 20519
## + property_type           16    345329 9121649 20826
## + bedrooms                 1    166560 9300418 20845
## + cancellation_policy      4    147637 9319341 20856
## + instant_bookable         1    121042 9345936 20858
## + bathrooms                1     74763 9392215 20870
## + number_of_reviews        1     53794 9413184 20876
## + guests_included          1     38644 9428334 20880
## + X                        1     10349 9456629 20887
## <none>                                 9466978 20888
## + minimum_nights           1      6866 9460113 20888
## + host_identity_verified   1      1012 9465966 20890
## + beds                     1       468 9466510 20890
## + host_is_superhost        1       179 9466799 20890
## + is_business_travel_ready  1         1 9466977 20890
## + bed_type                 4      4942 9462036 20895
##
## Step:  AIC=20519.11
## price ~ room_type + accommodates + neighborhood
##
##                           Df Sum of Sq     RSS   AIC
## + bedrooms                 1    353970 7678822 20407
## + property_type           16    270772 7762020 20464
## + cancellation_policy      4    191046 7841746 20466
## + instant_bookable         1    138697 7894095 20477
## + bathrooms                1     88977 7943815 20493
## + guests_included          1     81470 7951321 20495
## + number_of_reviews        1     33899 7998892 20510
## + minimum_nights           1     13282 8019509 20517
```

```
## + beds                      1     12465 8020327 20517
## <none>                                  8032792 20519
## + host_is_superhost         1      3930 8028862 20520
## + X                         1      1890 8030901 20521
## + is_business_travel_ready  1       978 8031814 20521
## + host_identity_verified    1         4 8032788 20521
## + bed_type                  4       487 8032305 20527
##
## Step:  AIC=20406.69
## price ~ room_type + accommodates + neighborhood + bedrooms
##
##                            Df Sum of Sq     RSS   AIC
## + property_type            16    274726 7404096 20346
## + cancellation_policy       4    172742 7506080 20357
## + instant_bookable          1    133193 7545629 20364
## + guests_included           1     79699 7599123 20382
## + bathrooms                 1     30843 7647978 20399
## + minimum_nights            1     29218 7649603 20399
## + number_of_reviews         1     18830 7659992 20403
## + host_is_superhost         1      6755 7672066 20407
## <none>                                  7678822 20407
## + X                         1      3337 7675485 20408
## + is_business_travel_ready  1       954 7677868 20408
## + beds                      1       798 7678024 20408
## + host_identity_verified    1       298 7678524 20409
## + bed_type                  4      2423 7676399 20414
##
## Step:  AIC=20346.19
## price ~ room_type + accommodates + neighborhood + bedrooms +
##     property_type
##
##                            Df Sum of Sq     RSS   AIC
## + cancellation_policy       4    155343 7248752 20300
## + instant_bookable          1    137533 7266562 20301
## + guests_included           1     71180 7332916 20324
## + minimum_nights            1     25664 7378431 20339
## + bathrooms                 1     24768 7379328 20340
## + number_of_reviews         1     16366 7387729 20343
## + host_is_superhost         1      6344 7397752 20346
## <none>                                  7404096 20346
## + X                         1      4646 7399450 20347
## + is_business_travel_ready  1      1836 7402260 20348
## + host_identity_verified    1       293 7403803 20348
## + beds                      1         8 7404088 20348
## + bed_type                  4      3012 7401083 20353
##
## Step:  AIC=20300.35
## price ~ room_type + accommodates + neighborhood + bedrooms +
##     property_type + cancellation_policy
##
##                            Df Sum of Sq     RSS   AIC
## + instant_bookable          1    121214 7127538 20260
## + guests_included           1     64392 7184361 20280
## + bathrooms                 1     33350 7215402 20291
```

```
## + number_of_reviews         1     16252 7232501 20297
## + minimum_nights            1     14770 7233983 20297
## + host_is_superhost         1      6312 7242440 20300
## + X                         1      6225 7242527 20300
## <none>                                 7248752 20300
## + is_business_travel_ready  1      3934 7244818 20301
## + host_identity_verified    1      2694 7246058 20301
## + beds                      1       152 7248600 20302
## + bed_type                  4      2031 7246721 20308
##
## Step:  AIC=20259.54
## price ~ room_type + accommodates + neighborhood + bedrooms +
##     property_type + cancellation_policy + instant_bookable
##
##                            Df Sum of Sq     RSS   AIC
## + guests_included           1     71043 7056496 20236
## + minimum_nights            1     24288 7103250 20253
## + bathrooms                 1     24025 7103513 20253
## + is_business_travel_ready  1     10230 7117308 20258
## + number_of_reviews         1      7556 7119982 20259
## + host_identity_verified    1      6616 7120922 20259
## <none>                                 7127538 20260
## + X                         1      4561 7122977 20260
## + host_is_superhost         1      4230 7123308 20260
## + beds                      1       163 7127375 20262
## + bed_type                  4      1840 7125698 20267
##
## Step:  AIC=20236.1
## price ~ room_type + accommodates + neighborhood + bedrooms +
##     property_type + cancellation_policy + instant_bookable +
##     guests_included
##
##                            Df Sum of Sq     RSS   AIC
## + bathrooms                 1     32231 7024265 20227
## + minimum_nights            1     25366 7031129 20229
## + number_of_reviews         1     10844 7045651 20234
## + host_identity_verified    1      7011 7049485 20236
## <none>                                 7056496 20236
## + is_business_travel_ready  1      4773 7051722 20236
## + X                         1      4530 7051966 20237
## + host_is_superhost         1      2009 7054486 20237
## + beds                      1      1528 7054967 20238
## + bed_type                  4      1584 7054911 20244
##
## Step:  AIC=20226.48
## price ~ room_type + accommodates + neighborhood + bedrooms +
##     property_type + cancellation_policy + instant_bookable +
##     guests_included + bathrooms
##
##                            Df Sum of Sq     RSS   AIC
## + minimum_nights            1   26895.3 6997369 20219
## + number_of_reviews         1    9730.4 7014534 20225
## + host_identity_verified    1    6887.1 7017378 20226
## + is_business_travel_ready  1    5534.4 7018730 20227
```

```
## <none>                                7024265 20227
## + X                       1    4356.0 7019909 20227
## + host_is_superhost       1    2222.4 7022042 20228
## + beds                    1    1090.2 7023174 20228
## + bed_type                4    1570.3 7022694 20234
##
## Step:  AIC=20218.74
## price ~ room_type + accommodates + neighborhood + bedrooms +
##     property_type + cancellation_policy + instant_bookable +
##     guests_included + bathrooms + minimum_nights
##
##                          Df Sum of Sq     RSS   AIC
## + number_of_reviews       1   12718.8 6984651 20216
## + host_identity_verified  1    7691.7 6989678 20218
## <none>                                6997369 20219
## + is_business_travel_ready  1    4388.0 6992981 20219
## + X                       1    3623.3 6993746 20219
## + host_is_superhost       1    2412.9 6994956 20220
## + beds                    1     722.4 6996647 20221
## + bed_type                4    1072.8 6996297 20226
##
## Step:  AIC=20216.12
## price ~ room_type + accommodates + neighborhood + bedrooms +
##     property_type + cancellation_policy + instant_bookable +
##     guests_included + bathrooms + minimum_nights + number_of_reviews
##
##                          Df Sum of Sq     RSS   AIC
## + is_business_travel_ready  1    8437.8 6976213 20215
## + host_is_superhost       1    7061.9 6977589 20216
## + host_identity_verified  1    5663.1 6978987 20216
## <none>                                6984651 20216
## + X                       1    4795.6 6979855 20216
## + beds                    1     731.7 6983919 20218
## + bed_type                4    1079.4 6983571 20224
##
## Step:  AIC=20215.05
## price ~ room_type + accommodates + neighborhood + bedrooms +
##     property_type + cancellation_policy + instant_bookable +
##     guests_included + bathrooms + minimum_nights + number_of_reviews +
##     is_business_travel_ready
##
##                        Df Sum of Sq     RSS   AIC
## + host_identity_verified  1    7033.2 6969180 20215
## <none>                              6976213 20215
## + host_is_superhost     1    4628.0 6971585 20215
## + X                     1    4525.2 6971688 20215
## + beds                  1    1110.5 6975102 20217
## + bed_type              4    1087.9 6975125 20223
##
## Step:  AIC=20214.49
## price ~ room_type + accommodates + neighborhood + bedrooms +
##     property_type + cancellation_policy + instant_bookable +
##     guests_included + bathrooms + minimum_nights + number_of_reviews +
##     is_business_travel_ready + host_identity_verified
```

```
##
##                      Df Sum of Sq     RSS   AIC
## + host_is_superhost  1    5779.8 6963400 20214
## <none>                           6969180 20215
## + X                  1    5068.1 6964112 20215
## + beds               1    1252.9 6967927 20216
## + bed_type           4    1240.9 6967939 20222
##
## Step:  AIC=20214.38
## price ~ room_type + accommodates + neighborhood + bedrooms +
##     property_type + cancellation_policy + instant_bookable +
##     guests_included + bathrooms + minimum_nights + number_of_reviews +
##     is_business_travel_ready + host_identity_verified + host_is_superhost
##
##            Df Sum of Sq     RSS   AIC
## <none>                  6963400 20214
## + X         1    5027.2 6958373 20215
## + beds      1    1466.6 6961933 20216
## + bed_type  4    1297.5 6962102 20222
```

```
# Results: price ~ room_type + accommodates + neighborhood + bedrooms + property_type + cancellation_po

# The same predictors were obtained when "backward" and "both" directions for steps selctions as well.

# GAM based on the above predictors
gam.var2 <- gam(price ~ room_type + accommodates + neighborhood + bedrooms + property_type + cancellati
summary(gam.var2)
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## price ~ room_type + accommodates + neighborhood + bedrooms +
##     property_type + cancellation_policy + instant_bookable +
##     s(guests_included, bs = "cr") + s(bathrooms, bs = "cr") +
##     s(minimum_nights, bs = "cr") + s(number_of_reviews, bs = "cr") +
##     is_business_travel_ready + host_identity_verified + host_is_superhost
##
## Parametric coefficients:
##                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)                         97.6875     5.8839  16.602  < 2e-16
## room_typePrivate room              -58.5335     3.2102 -18.234  < 2e-16
## room_typeShared room               -67.4184     9.7726  -6.899 6.64e-12
## accommodates                         6.1220     0.9721   6.298 3.56e-10
## neighborhoodBack Bay                83.2301     5.9168  14.067  < 2e-16
## neighborhoodBay Village             49.9878    14.8640   3.363 0.000783
## neighborhoodBeacon Hill             71.4754     6.2611  11.416  < 2e-16
## neighborhoodBrighton                 7.3488     5.9401   1.237 0.216145
## neighborhoodCharlestown             56.5329     7.8425   7.209 7.48e-13
## neighborhoodChinatown               48.9366     8.1261   6.022 1.98e-09
## neighborhoodDorchester               4.8598     5.6759   0.856 0.391959
## neighborhoodDowntown                73.4380     6.3226  11.615  < 2e-16
## neighborhoodEast Boston             10.9405     6.1863   1.769 0.077099
## neighborhoodFenway                  41.5173     5.9086   7.027 2.72e-12
```

```
## neighborhoodHyde Park               -10.4942    11.4873  -0.914 0.361047
## neighborhoodJamaica Plain            11.6964     5.5812   2.096 0.036214
## neighborhoodLeather District        105.1790    27.5033   3.824 0.000134
## neighborhoodLongwood Medical Area    54.9176    26.9565   2.037 0.041730
## neighborhoodMattapan                -10.1929    13.2371  -0.770 0.441356
## neighborhoodMission Hill             12.3863     7.5101   1.649 0.099213
## neighborhoodNorth End                25.4530     7.1687   3.551 0.000392
## neighborhoodRoslindale              -14.6916     8.1721  -1.798 0.072334
## neighborhoodRoxbury                   9.4433     6.3623   1.484 0.137866
## neighborhoodSouth Boston             32.5004     6.2940   5.164 2.61e-07
## neighborhoodSouth Boston Waterfront  91.4593    10.1349   9.024  < 2e-16
## neighborhoodSouth End                62.5618     5.8812  10.638  < 2e-16
## neighborhoodWest End                 49.9164    11.2268   4.446 9.13e-06
## neighborhoodWest Roxbury             -2.9702     9.6720  -0.307 0.758797
## bedrooms                             20.7472     2.1618   9.597  < 2e-16
## property_typeBed & Breakfast         16.8029    14.0051   1.200 0.230344
## property_typeBoat                    26.8314    24.0694   1.115 0.265065
## property_typeBoutique hotel         -52.8776    31.5254  -1.677 0.093610
## property_typeCondominium             13.8768     3.7636   3.687 0.000232
## property_typeDorm                   -21.1384    53.0228  -0.399 0.690174
## property_typeGuest suite             31.1185    21.7520   1.431 0.152670
## property_typeGuesthouse              91.4793    30.6245   2.987 0.002844
## property_typeHostel                 -38.4091    54.2395  -0.708 0.478925
## property_typeHouse                    5.5204     3.4082   1.620 0.105413
## property_typeIn-law                 -20.5059    23.9582  -0.856 0.392134
## property_typeLoft                    27.7601    12.0450   2.305 0.021266
## property_typeOther                   55.4374     9.6794   5.727 1.14e-08
## property_typeServiced apartment     -34.6741    53.0548  -0.654 0.513461
## property_typeTimeshare              218.7057    53.1553   4.114 4.01e-05
## property_typeTownhouse               11.6491     8.7768   1.327 0.184542
## property_typeVilla                   22.7554    20.1767   1.128 0.259510
## cancellation_policymoderate           7.5854     3.1921   2.376 0.017564
## cancellation_policystrict            -8.0366     2.8229  -2.847 0.004450
## cancellation_policysuper_strict_30   40.5316    14.0493   2.885 0.003949
## cancellation_policysuper_strict_60  100.1431    53.1929   1.883 0.059866
## instant_bookablet                   -14.9786     2.3365  -6.411 1.73e-10
## is_business_travel_readyt             5.4584     3.4315   1.591 0.111809
## host_identity_verifiedt              -3.8760     2.2862  -1.695 0.090119
## host_is_superhostt                    3.8657     2.9080   1.329 0.183869
##
## (Intercept)                         ***
## room_typePrivate room               ***
## room_typeShared room                ***
## accommodates                        ***
## neighborhoodBack Bay                ***
## neighborhoodBay Village             ***
## neighborhoodBeacon Hill             ***
## neighborhoodBrighton
## neighborhoodCharlestown             ***
## neighborhoodChinatown               ***
## neighborhoodDorchester
## neighborhoodDowntown                ***
## neighborhoodEast Boston             .
## neighborhoodFenway                  ***
```

```
## neighborhoodHyde Park
## neighborhoodJamaica Plain           *
## neighborhoodLeather District        ***
## neighborhoodLongwood Medical Area   *
## neighborhoodMattapan
## neighborhoodMission Hill            .
## neighborhoodNorth End               ***
## neighborhoodRoslindale              .
## neighborhoodRoxbury
## neighborhoodSouth Boston            ***
## neighborhoodSouth Boston Waterfront ***
## neighborhoodSouth End               ***
## neighborhoodWest End                ***
## neighborhoodWest Roxbury
## bedrooms                            ***
## property_typeBed & Breakfast
## property_typeBoat
## property_typeBoutique hotel         .
## property_typeCondominium            ***
## property_typeDorm
## property_typeGuest suite
## property_typeGuesthouse             **
## property_typeHostel
## property_typeHouse
## property_typeIn-law
## property_typeLoft                   *
## property_typeOther                  ***
## property_typeServiced apartment
## property_typeTimeshare              ***
## property_typeTownhouse
## property_typeVilla
## cancellation_policymoderate         *
## cancellation_policystrict           **
## cancellation_policysuper_strict_30  **
## cancellation_policysuper_strict_60  .
## instant_bookablet                   ***
## is_business_travel_readyt
## host_identity_verifiedt             .
## host_is_superhostt
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                        edf Ref.df      F  p-value
## s(guests_included)   3.682  4.467  8.809 1.49e-07 ***
## s(bathrooms)         1.024  1.048 11.944 0.000525 ***
## s(minimum_nights)    4.947  5.707  3.798 0.001862 **
## s(number_of_reviews) 1.803  2.272  3.231 0.036207 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.609   Deviance explained = 61.9%
## -REML =  13477  Scale est. = 2778.7    n = 2539
```

```r
# R^2: 0.609

gam.var2.rmse <- rmse(boston.data.model_selection, gam.var2)
gam.var2.rmse # 58.11913
```

```
## [1] 58.11913
```

Shrinkage method within GAM

```r
gam.var3 <- gam(price ~ host_is_superhost + host_identity_verified + neighborhood + property_type + roo
summary(gam.var3)
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## price ~ host_is_superhost + host_identity_verified + neighborhood +
##     property_type + room_type + s(accommodates, bs = "cs") +
##     s(bathrooms, bs = "cs") + s(bedrooms, k = 5, bs = "cs") +
##     s(beds, bs = "cs") + bed_type + s(guests_included, bs = "cs") +
##     s(minimum_nights, bs = "cs") + s(number_of_reviews, bs = "cs") +
##     instant_bookable + is_business_travel_ready + cancellation_policy
##
## Parametric coefficients:
##                                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)                           143.0699    12.8311  11.150  < 2e-16
## host_is_superhostt                      3.6971     2.8833   1.282 0.199880
## host_identity_verifiedt                -4.1873     2.2990  -1.821 0.068672
## neighborhoodBack Bay                   82.7494     5.9169  13.985  < 2e-16
## neighborhoodBay Village                51.2601    14.8473   3.452 0.000565
## neighborhoodBeacon Hill                71.6485     6.2707  11.426  < 2e-16
## neighborhoodBrighton                    7.1954     5.9515   1.209 0.226770
## neighborhoodCharlestown                55.4652     7.8520   7.064 2.10e-12
## neighborhoodChinatown                  48.7407     8.1604   5.973 2.67e-09
## neighborhoodDorchester                  5.1311     5.7621   0.890 0.373290
## neighborhoodDowntown                   73.5038     6.3479  11.579  < 2e-16
## neighborhoodEast Boston                 9.1249     6.1957   1.473 0.140936
## neighborhoodFenway                     42.8928     5.9205   7.245 5.76e-13
## neighborhoodHyde Park                 -10.4673    11.5042  -0.910 0.362983
## neighborhoodJamaica Plain              10.9255     5.5869   1.956 0.050629
## neighborhoodLeather District          103.5865    27.4796   3.770 0.000167
## neighborhoodLongwood Medical Area      58.5869    26.8893   2.179 0.029439
## neighborhoodMattapan                  -11.0450    13.2234  -0.835 0.403650
## neighborhoodMission Hill               13.3995     7.5247   1.781 0.075077
## neighborhoodNorth End                  25.4344     7.1599   3.552 0.000389
## neighborhoodRoslindale                -14.1585     8.2079  -1.725 0.084655
## neighborhoodRoxbury                     8.6691     6.3766   1.360 0.174104
## neighborhoodSouth Boston               33.2277     6.2935   5.280 1.41e-07
## neighborhoodSouth Boston Waterfront    91.5142    10.1392   9.026  < 2e-16
## neighborhoodSouth End                  62.2599     5.8952  10.561  < 2e-16
## neighborhoodWest End                   49.5433    11.1412   4.447 9.10e-06
## neighborhoodWest Roxbury               -4.5993     9.6646  -0.476 0.634191
```

```
## property_typeBed & Breakfast         15.8409    13.9800   1.133 0.257276
## property_typeBoat                    28.7391    24.0674   1.194 0.232550
## property_typeBoutique hotel         -51.5961    31.4758  -1.639 0.101292
## property_typeCondominium             13.0156     3.7669   3.455 0.000559
## property_typeDorm                   -25.8631    52.9824  -0.488 0.625490
## property_typeGuest suite             31.0022    21.7553   1.425 0.154272
## property_typeGuesthouse              92.6975    30.5928   3.030 0.002471
## property_typeHostel                 -33.9783    54.9511  -0.618 0.536410
## property_typeHouse                    5.1960     3.4120   1.523 0.127917
## property_typeIn-law                 -21.7541    23.9380  -0.909 0.363560
## property_typeLoft                    27.7543    12.0470   2.304 0.021315
## property_typeOther                   55.4651     9.6472   5.749 1.01e-08
## property_typeServiced apartment     -29.6876    53.0053  -0.560 0.575471
## property_typeTimeshare              218.5677    53.0527   4.120 3.92e-05
## property_typeTownhouse               12.2324     8.7882   1.392 0.164076
## property_typeVilla                   24.1438    20.1632   1.197 0.231256
## room_typePrivate room               -55.1765     3.4622 -15.937  < 2e-16
## room_typeShared room                -64.6100    10.4119  -6.205 6.38e-10
## bed_typeCouch                        13.1526    29.4240   0.447 0.654913
## bed_typeFuton                         6.6351    16.8786   0.393 0.694273
## bed_typePull-out Sofa                 3.7651    18.7918   0.200 0.841217
## bed_typeReal Bed                      0.2398    11.6532   0.021 0.983587
## instant_bookablet                   -16.1252     2.3274  -6.928 5.41e-12
## is_business_travel_readyt             6.2816     3.4218   1.836 0.066510
## cancellation_policymoderate           6.7307     3.1877   2.111 0.034834
## cancellation_policystrict            -8.2661     2.7929  -2.960 0.003109
## cancellation_policysuper_strict_30   41.7982    14.0372   2.978 0.002933
## cancellation_policysuper_strict_60   97.2346    53.2487   1.826 0.067964
##
## (Intercept)                         ***
## host_is_superhostt
## host_identity_verifiedt             .
## neighborhoodBack Bay                ***
## neighborhoodBay Village             ***
## neighborhoodBeacon Hill             ***
## neighborhoodBrighton
## neighborhoodCharlestown             ***
## neighborhoodChinatown               ***
## neighborhoodDorchester
## neighborhoodDowntown                ***
## neighborhoodEast Boston
## neighborhoodFenway                  ***
## neighborhoodHyde Park
## neighborhoodJamaica Plain           .
## neighborhoodLeather District        ***
## neighborhoodLongwood Medical Area   *
## neighborhoodMattapan
## neighborhoodMission Hill            .
## neighborhoodNorth End               ***
## neighborhoodRoslindale              .
## neighborhoodRoxbury
## neighborhoodSouth Boston            ***
## neighborhoodSouth Boston Waterfront ***
## neighborhoodSouth End               ***
```

```
## neighborhoodWest End                ***
## neighborhoodWest Roxbury
## property_typeBed & Breakfast
## property_typeBoat
## property_typeBoutique hotel
## property_typeCondominium            ***
## property_typeDorm
## property_typeGuest suite
## property_typeGuesthouse             **
## property_typeHostel
## property_typeHouse
## property_typeIn-law
## property_typeLoft                   *
## property_typeOther                  ***
## property_typeServiced apartment
## property_typeTimeshare              ***
## property_typeTownhouse
## property_typeVilla
## room_typePrivate room               ***
## room_typeShared room                ***
## bed_typeCouch
## bed_typeFuton
## bed_typePull-out Sofa
## bed_typeReal Bed
## instant_bookablet                   ***
## is_business_travel_readyt           .
## cancellation_policymoderate         *
## cancellation_policystrict           **
## cancellation_policysuper_strict_30  **
## cancellation_policysuper_strict_60  .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                          edf Ref.df      F  p-value
## s(accommodates)      3.66005      9  4.835 7.56e-11 ***
## s(bathrooms)         1.06148      8  1.408 0.000446 ***
## s(bedrooms)          2.90382      4 26.724  < 2e-16 ***
## s(beds)              0.01323      9  0.001 0.375208
## s(guests_included)   2.76851      9  3.588 2.64e-08 ***
## s(minimum_nights)    1.47237      9  0.954 0.002546 **
## s(number_of_reviews) 0.99390      9  0.708 0.007460 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =   0.61   Deviance explained =   62%
## -REML =  13487  Scale est. = 2773.3    n = 2539
```

```r
# R^2: 0.610

gam.var3.rmse <- rmse(boston.data.model_selection, gam.var3)
gam.var3.rmse # 55.14769
```

```
## [1] 55.14769
```

Since, the shrinkage method of variable selection has the best RMSE, it will be adopted as the variable selection method henceforth.

GAM on all the datasets

Original dataset

```r
gam.neighborhood <- gam(price ~ host_is_superhost + host_identity_verified + neighborhood + property_typ
summary(gam.neighborhood)
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## price ~ host_is_superhost + host_identity_verified + neighborhood +
##     property_type + room_type + s(accommodates, bs = "cs") +
##     s(bathrooms, bs = "cs") + s(bedrooms, k = 5, bs = "cs") +
##     s(beds, bs = "cs") + bed_type + s(guests_included, bs = "cs") +
##     s(minimum_nights, bs = "cs") + s(number_of_reviews, bs = "cs") +
##     instant_bookable + is_business_travel_ready + cancellation_policy
##
## Parametric coefficients:
##                                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)                          143.0699    12.8311  11.150  < 2e-16
## host_is_superhostt                     3.6971     2.8833   1.282 0.199880
## host_identity_verifiedt               -4.1873     2.2990  -1.821 0.068672
## neighborhoodBack Bay                  82.7494     5.9169  13.985  < 2e-16
## neighborhoodBay Village               51.2601    14.8473   3.452 0.000565
## neighborhoodBeacon Hill               71.6485     6.2707  11.426  < 2e-16
## neighborhoodBrighton                   7.1954     5.9515   1.209 0.226770
## neighborhoodCharlestown               55.4652     7.8520   7.064 2.10e-12
## neighborhoodChinatown                 48.7407     8.1604   5.973 2.67e-09
## neighborhoodDorchester                 5.1311     5.7621   0.890 0.373290
## neighborhoodDowntown                  73.5038     6.3479  11.579  < 2e-16
## neighborhoodEast Boston                9.1249     6.1957   1.473 0.140936
## neighborhoodFenway                    42.8928     5.9205   7.245 5.76e-13
## neighborhoodHyde Park                -10.4673    11.5042  -0.910 0.362983
## neighborhoodJamaica Plain             10.9255     5.5869   1.956 0.050629
## neighborhoodLeather District         103.5865    27.4796   3.770 0.000167
## neighborhoodLongwood Medical Area     58.5869    26.8893   2.179 0.029439
## neighborhoodMattapan                 -11.0450    13.2234  -0.835 0.403650
## neighborhoodMission Hill              13.3995     7.5247   1.781 0.075077
## neighborhoodNorth End                 25.4344     7.1599   3.552 0.000389
## neighborhoodRoslindale               -14.1585     8.2079  -1.725 0.084655
## neighborhoodRoxbury                    8.6691     6.3766   1.360 0.174104
## neighborhoodSouth Boston              33.2277     6.2935   5.280 1.41e-07
## neighborhoodSouth Boston Waterfront   91.5142    10.1392   9.026  < 2e-16
## neighborhoodSouth End                 62.2599     5.8952  10.561  < 2e-16
## neighborhoodWest End                  49.5433    11.1412   4.447 9.10e-06
## neighborhoodWest Roxbury              -4.5993     9.6646  -0.476 0.634191
## property_typeBed & Breakfast          15.8409    13.9800   1.133 0.257276
## property_typeBoat                     28.7391    24.0674   1.194 0.232550
```

```
## property_typeBoutique hotel         -51.5961    31.4758  -1.639 0.101292
## property_typeCondominium             13.0156     3.7669   3.455 0.000559
## property_typeDorm                   -25.8631    52.9824  -0.488 0.625490
## property_typeGuest suite             31.0022    21.7553   1.425 0.154272
## property_typeGuesthouse              92.6975    30.5928   3.030 0.002471
## property_typeHostel                 -33.9783    54.9511  -0.618 0.536410
## property_typeHouse                    5.1960     3.4120   1.523 0.127917
## property_typeIn-law                 -21.7541    23.9380  -0.909 0.363560
## property_typeLoft                    27.7543    12.0470   2.304 0.021315
## property_typeOther                   55.4651     9.6472   5.749 1.01e-08
## property_typeServiced apartment     -29.6876    53.0053  -0.560 0.575471
## property_typeTimeshare              218.5677    53.0527   4.120 3.92e-05
## property_typeTownhouse               12.2324     8.7882   1.392 0.164076
## property_typeVilla                   24.1438    20.1632   1.197 0.231256
## room_typePrivate room               -55.1765     3.4622 -15.937  < 2e-16
## room_typeShared room                -64.6100    10.4119  -6.205 6.38e-10
## bed_typeCouch                        13.1526    29.4240   0.447 0.654913
## bed_typeFuton                         6.6351    16.8786   0.393 0.694273
## bed_typePull-out Sofa                 3.7651    18.7918   0.200 0.841217
## bed_typeReal Bed                      0.2398    11.6532   0.021 0.983587
## instant_bookablet                   -16.1252     2.3274  -6.928 5.41e-12
## is_business_travel_readyt             6.2816     3.4218   1.836 0.066510
## cancellation_policymoderate           6.7307     3.1877   2.111 0.034834
## cancellation_policystrict            -8.2661     2.7929  -2.960 0.003109
## cancellation_policysuper_strict_30   41.7982    14.0372   2.978 0.002933
## cancellation_policysuper_strict_60   97.2346    53.2487   1.826 0.067964
##
## (Intercept)                         ***
## host_is_superhostt
## host_identity_verifiedt             .
## neighborhoodBack Bay                ***
## neighborhoodBay Village             ***
## neighborhoodBeacon Hill             ***
## neighborhoodBrighton
## neighborhoodCharlestown             ***
## neighborhoodChinatown               ***
## neighborhoodDorchester
## neighborhoodDowntown                ***
## neighborhoodEast Boston
## neighborhoodFenway                  ***
## neighborhoodHyde Park
## neighborhoodJamaica Plain           .
## neighborhoodLeather District        ***
## neighborhoodLongwood Medical Area   *
## neighborhoodMattapan
## neighborhoodMission Hill            .
## neighborhoodNorth End               ***
## neighborhoodRoslindale              .
## neighborhoodRoxbury
## neighborhoodSouth Boston            ***
## neighborhoodSouth Boston Waterfront ***
## neighborhoodSouth End               ***
## neighborhoodWest End                ***
## neighborhoodWest Roxbury
```

```
## property_typeBed & Breakfast
## property_typeBoat
## property_typeBoutique hotel
## property_typeCondominium            ***
## property_typeDorm
## property_typeGuest suite
## property_typeGuesthouse             **
## property_typeHostel
## property_typeHouse
## property_typeIn-law
## property_typeLoft                   *
## property_typeOther                  ***
## property_typeServiced apartment
## property_typeTimeshare              ***
## property_typeTownhouse
## property_typeVilla
## room_typePrivate room               ***
## room_typeShared room                ***
## bed_typeCouch
## bed_typeFuton
## bed_typePull-out Sofa
## bed_typeReal Bed
## instant_bookablet                   ***
## is_business_travel_readyt           .
## cancellation_policymoderate         *
## cancellation_policystrict           **
## cancellation_policysuper_strict_30  **
## cancellation_policysuper_strict_60  .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                         edf Ref.df      F  p-value
## s(accommodates)      3.66005      9  4.835 7.56e-11 ***
## s(bathrooms)         1.06148      8  1.408 0.000446 ***
## s(bedrooms)          2.90382      4 26.724  < 2e-16 ***
## s(beds)              0.01323      9  0.001 0.375208
## s(guests_included)   2.76851      9  3.588 2.64e-08 ***
## s(minimum_nights)    1.47237      9  0.954 0.002546 **
## s(number_of_reviews) 0.99390      9  0.708 0.007460 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =   0.61   Deviance explained =   62%
## -REML =  13487  Scale est. = 2773.3    n = 2539
```

```
# R^2: 0.610

gam.neighborhood.rmse <- rmse(boston.data.model_selection, gam.neighborhood)
gam.neighborhood.rmse # 55.14769
```

```
## [1] 55.14769
```

Distance to both airport and downtown

```r
gam.dboth <- gam(price ~ host_is_superhost + host_identity_verified + property_type + room_type + s(acco
summary(gam.dboth)
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## price ~ host_is_superhost + host_identity_verified + property_type +
##     room_type + s(accommodates, bs = "cs") + s(bathrooms, bs = "cs") +
##     s(bedrooms, k = 5, bs = "cs") + +s(beds, bs = "cs") + bed_type +
##     s(guests_included, bs = "cs") + s(minimum_nights, bs = "cs") +
##     s(number_of_reviews, bs = "cs") + instant_bookable + is_business_travel_ready +
##     cancellation_policy + s(ddowntown, bs = "cs") + s(dairport,
##     bs = "cs")
##
## Parametric coefficients:
##                                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)                           179.820     12.040  14.935  < 2e-16
## host_is_superhostt                      3.064      2.902   1.056 0.291151
## host_identity_verifiedt                -4.503      2.313  -1.947 0.051666
## property_typeBed & Breakfast           17.782     14.082   1.263 0.206799
## property_typeBoat                      30.327     24.329   1.247 0.212689
## property_typeBoutique hotel           -50.938     31.862  -1.599 0.110016
## property_typeCondominium               12.223      3.788   3.227 0.001269
## property_typeDorm                     -22.933     53.598  -0.428 0.668786
## property_typeGuest suite               28.552     21.991   1.298 0.194281
## property_typeGuesthouse                87.730     30.913   2.838 0.004577
## property_typeHostel                   -37.647     55.593  -0.677 0.498349
## property_typeHouse                      3.475      3.418   1.017 0.309417
## property_typeIn-law                   -26.717     24.178  -1.105 0.269258
## property_typeLoft                      27.756     11.891   2.334 0.019668
## property_typeOther                     54.536      9.639   5.658 1.71e-08
## property_typeServiced apartment       -33.653     53.653  -0.627 0.530567
## property_typeTimeshare                221.508     53.640   4.130 3.75e-05
## property_typeTownhouse                  9.214      8.845   1.042 0.297664
## property_typeVilla                     23.443     20.371   1.151 0.249908
## room_typePrivate room                 -57.901      3.455 -16.760  < 2e-16
## room_typeShared room                  -68.185     10.502  -6.493 1.01e-10
## bed_typeCouch                           4.670     29.654   0.157 0.874873
## bed_typeFuton                           3.360     16.785   0.200 0.841350
## bed_typePull-out Sofa                  -1.618     18.817  -0.086 0.931485
## bed_typeReal Bed                       -1.763     11.612  -0.152 0.879317
## instant_bookablet                     -15.601      2.331  -6.691 2.72e-11
## is_business_travel_readyt               5.600      3.450   1.623 0.104689
## cancellation_policymoderate             6.858      3.216   2.132 0.033092
## cancellation_policystrict              -8.544      2.814  -3.036 0.002419
## cancellation_policysuper_strict_30     48.571     14.146   3.434 0.000605
## cancellation_policysuper_strict_60     93.666     53.872   1.739 0.082218
##
## (Intercept)                          ***
## host_is_superhostt
```

```
## host_identity_verifiedt            .
## property_typeBed & Breakfast
## property_typeBoat
## property_typeBoutique hotel
## property_typeCondominium           **
## property_typeDorm
## property_typeGuest suite
## property_typeGuesthouse            **
## property_typeHostel
## property_typeHouse
## property_typeIn-law
## property_typeLoft                  *
## property_typeOther                 ***
## property_typeServiced apartment
## property_typeTimeshare             ***
## property_typeTownhouse
## property_typeVilla
## room_typePrivate room              ***
## room_typeShared room               ***
## bed_typeCouch
## bed_typeFuton
## bed_typePull-out Sofa
## bed_typeReal Bed
## instant_bookablet                  ***
## is_business_travel_readyt
## cancellation_policymoderate        *
## cancellation_policystrict          **
## cancellation_policysuper_strict_30 ***
## cancellation_policysuper_strict_60 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                          edf Ref.df      F  p-value
## s(accommodates)      3.79403      9  4.835 1.00e-10 ***
## s(bathrooms)         1.06742      8  1.446 0.000375 ***
## s(bedrooms)          2.81143      4 24.763  < 2e-16 ***
## s(beds)              0.01076      9  0.001 0.473394
## s(guests_included)   1.77026      9  3.176 4.35e-08 ***
## s(minimum_nights)    1.38292      9  0.808 0.005042 **
## s(number_of_reviews) 1.07710      9  0.940 0.002481 **
## s(ddowntown)         5.18910      9  3.603 2.70e-08 ***
## s(dairport)          5.31413      9 10.888  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =    0.6   Deviance explained = 60.9%
## -REML =  13624  Scale est. = 2843.1    n = 2539
```

```
# R^2: 0.600

gam.dboth.rmspe <- rmse(boston.dboth.model_selection, gam.dboth)
gam.dboth.rmspe # 55.77279
```

```
## [1] 55.77279
```

Distance to airport

```r
gam.dairport <- gam(price ~ host_is_superhost + host_identity_verified + property_type + room_type + s(a
summary(gam.dairport)
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## price ~ host_is_superhost + host_identity_verified + property_type +
##     room_type + s(accommodates, bs = "cs") + s(bathrooms, bs = "cs") +
##     s(bedrooms, k = 5, bs = "cs") + bed_type + s(guests_included,
##     bs = "cs") + s(minimum_nights, bs = "cs") + s(number_of_reviews,
##     bs = "cs") + instant_bookable + is_business_travel_ready +
##     cancellation_policy + s(dairport, bs = "cs")
##
## Parametric coefficients:
##                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)                         180.312     12.102  14.900  < 2e-16
## host_is_superhostt                    2.378      2.917   0.815 0.414965
## host_identity_verifiedt              -5.056      2.320  -2.179 0.029392
## property_typeBed & Breakfast         18.890     14.156   1.334 0.182195
## property_typeBoat                    17.969     24.184   0.743 0.457541
## property_typeBoutique hotel         -52.989     32.047  -1.653 0.098356
## property_typeCondominium              9.431      3.772   2.501 0.012464
## property_typeDorm                   -20.989     53.921  -0.389 0.697118
## property_typeGuest suite             26.397     22.112   1.194 0.232680
## property_typeGuesthouse              87.230     31.093   2.805 0.005063
## property_typeHostel                 -51.621     55.806  -0.925 0.355053
## property_typeHouse                    2.028      3.420   0.593 0.553278
## property_typeIn-law                 -30.282     24.310  -1.246 0.213004
## property_typeLoft                    29.828     11.915   2.503 0.012366
## property_typeOther                   54.727      9.683   5.652 1.77e-08
## property_typeServiced apartment     -35.817     53.976  -0.664 0.507023
## property_typeTimeshare              225.376     53.903   4.181 3.00e-05
## property_typeTownhouse                8.028      8.888   0.903 0.366462
## property_typeVilla                   24.413     20.481   1.192 0.233375
## room_typePrivate room               -59.651      3.454 -17.271  < 2e-16
## room_typeShared room                -70.408     10.548  -6.675 3.04e-11
## bed_typeCouch                         6.325     29.815   0.212 0.832007
## bed_typeFuton                         2.384     16.874   0.141 0.887663
## bed_typePull-out Sofa                -2.905     18.912  -0.154 0.877921
## bed_typeReal Bed                     -1.224     11.670  -0.105 0.916467
## instant_bookablet                   -15.378      2.341  -6.570 6.10e-11
## is_business_travel_readyt             5.550      3.472   1.599 0.110048
## cancellation_policymoderate           7.650      3.231   2.367 0.017988
## cancellation_policystrict            -7.738      2.822  -2.742 0.006145
## cancellation_policysuper_strict_30   52.906     14.186   3.729 0.000196
## cancellation_policysuper_strict_60   84.551     54.120   1.562 0.118349
##
## (Intercept)                        ***
## host_is_superhostt
## host_identity_verifiedt            *
```

```
## property_typeBed & Breakfast
## property_typeBoat
## property_typeBoutique hotel        .
## property_typeCondominium           *
## property_typeDorm
## property_typeGuest suite
## property_typeGuesthouse            **
## property_typeHostel
## property_typeHouse
## property_typeIn-law
## property_typeLoft                  *
## property_typeOther                 ***
## property_typeServiced apartment
## property_typeTimeshare             ***
## property_typeTownhouse
## property_typeVilla
## room_typePrivate room              ***
## room_typeShared room               ***
## bed_typeCouch
## bed_typeFuton
## bed_typePull-out Sofa
## bed_typeReal Bed
## instant_bookablet                  ***
## is_business_travel_readyt
## cancellation_policymoderate        *
## cancellation_policystrict          **
## cancellation_policysuper_strict_30 ***
## cancellation_policysuper_strict_60
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                        edf Ref.df      F  p-value
## s(accommodates)      3.711      9  4.848 7.89e-11 ***
## s(bathrooms)         1.065      8  1.418 0.000428 ***
## s(bedrooms)          2.754      4 21.536  < 2e-16 ***
## s(guests_included)   2.834      9  3.480 5.24e-08 ***
## s(minimum_nights)    1.311      9  0.680 0.009689 **
## s(number_of_reviews) 1.066      9  0.882 0.003313 **
## s(dairport)          7.051      9 48.773  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.596   Deviance explained = 60.4%
## -REML =  13632  Scale est. = 2876.8    n = 2539
```

```r
# R^2: 0.596

gam.dairport.rmse <- rmse(boston.dairport.model_selection, gam.dairport)
gam.dairport.rmse # 56.23814
```

```
## [1] 56.23814
```

Distance to downtown

```
gam.ddowntown <- gam(price ~ host_is_superhost + host_identity_verified + property_type + room_type + s
summary(gam.ddowntown)
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## price ~ host_is_superhost + host_identity_verified + property_type +
##     room_type + s(accommodates, bs = "cs") + s(bathrooms, bs = "cs") +
##     s(bedrooms, k = 5, bs = "cs") + bed_type + s(guests_included,
##     bs = "cs") + s(minimum_nights, bs = "cs") + s(number_of_reviews,
##     bs = "cs") + instant_bookable + is_business_travel_ready +
##     cancellation_policy + s(ddowntown, bs = "cs")
##
## Parametric coefficients:
##                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)                         182.833     12.301  14.864  < 2e-16
## host_is_superhostt                    3.934      2.957   1.330 0.183501
## host_identity_verifiedt              -4.507      2.345  -1.922 0.054752
## property_typeBed & Breakfast         23.477     14.332   1.638 0.101521
## property_typeBoat                    40.677     24.515   1.659 0.097179
## property_typeBoutique hotel         -67.487     32.257  -2.092 0.036527
## property_typeCondominium             12.078      3.826   3.157 0.001612
## property_typeDorm                   -22.427     54.623  -0.411 0.681418
## property_typeGuest suite             28.527     22.408   1.273 0.203110
## property_typeGuesthouse              92.001     31.506   2.920 0.003530
## property_typeHostel                 -49.630     56.658  -0.876 0.381131
## property_typeHouse                    1.899      3.458   0.549 0.582951
## property_typeIn-law                 -30.362     24.638  -1.232 0.217952
## property_typeLoft                    24.668     12.087   2.041 0.041369
## property_typeOther                   53.670      9.847   5.450 5.52e-08
## property_typeServiced apartment     -59.294     54.535  -1.087 0.277019
## property_typeTimeshare              221.426     54.754   4.044 5.41e-05
## property_typeTownhouse               12.423      9.004   1.380 0.167773
## property_typeVilla                   22.211     20.764   1.070 0.284850
## room_typePrivate room               -60.755      3.513 -17.294  < 2e-16
## room_typeShared room                -70.086     10.685  -6.559 6.55e-11
## bed_typeCouch                         1.102     30.231   0.036 0.970920
## bed_typeFuton                         2.909     17.138   0.170 0.865209
## bed_typePull-out Sofa                -3.651     19.196  -0.190 0.849182
## bed_typeReal Bed                     -3.039     11.872  -0.256 0.797984
## instant_bookablet                   -15.056      2.386  -6.311 3.27e-10
## is_business_travel_readyt             4.788      3.512   1.363 0.172920
## cancellation_policymoderate           5.421      3.279   1.653 0.098370
## cancellation_policystrict            -9.105      2.886  -3.155 0.001627
## cancellation_policysuper_strict_30   48.182     14.392   3.348 0.000826
## cancellation_policysuper_strict_60   84.447     54.837   1.540 0.123697
##
## (Intercept)                        ***
## host_is_superhostt
## host_identity_verifiedt            .
```

```
## property_typeBed & Breakfast
## property_typeBoat                    .
## property_typeBoutique hotel          *
## property_typeCondominium             **
## property_typeDorm
## property_typeGuest suite
## property_typeGuesthouse              **
## property_typeHostel
## property_typeHouse
## property_typeIn-law
## property_typeLoft                    *
## property_typeOther                   ***
## property_typeServiced apartment
## property_typeTimeshare               ***
## property_typeTownhouse
## property_typeVilla
## room_typePrivate room                ***
## room_typeShared room                 ***
## bed_typeCouch
## bed_typeFuton
## bed_typePull-out Sofa
## bed_typeReal Bed
## instant_bookablet                    ***
## is_business_travel_readyt
## cancellation_policymoderate          .
## cancellation_policystrict            **
## cancellation_policysuper_strict_30 ***
## cancellation_policysuper_strict_60
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                         edf Ref.df      F  p-value
## s(accommodates)       3.643      9  4.900 5.03e-11 ***
## s(bathrooms)          1.086      8  1.581 0.000209 ***
## s(bedrooms)           2.623      4 18.720  < 2e-16 ***
## s(guests_included)    1.439      9  3.024 7.84e-08 ***
## s(minimum_nights)     4.821      9  1.800 0.003453 **
## s(number_of_reviews) 1.150      9  1.446 0.000201 ***
## s(ddowntown)          4.621      9 39.472  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.585   Deviance explained = 59.3%
## -REML =  13662  Scale est. = 2954.7    n = 2539
```

```
# R^2: 0.585

gam.ddowntown.rmse <- rmse(boston.ddowntown.model_selection, gam.ddowntown)
gam.ddowntown.rmse # 58.05393
```

```
## [1] 58.05393
```

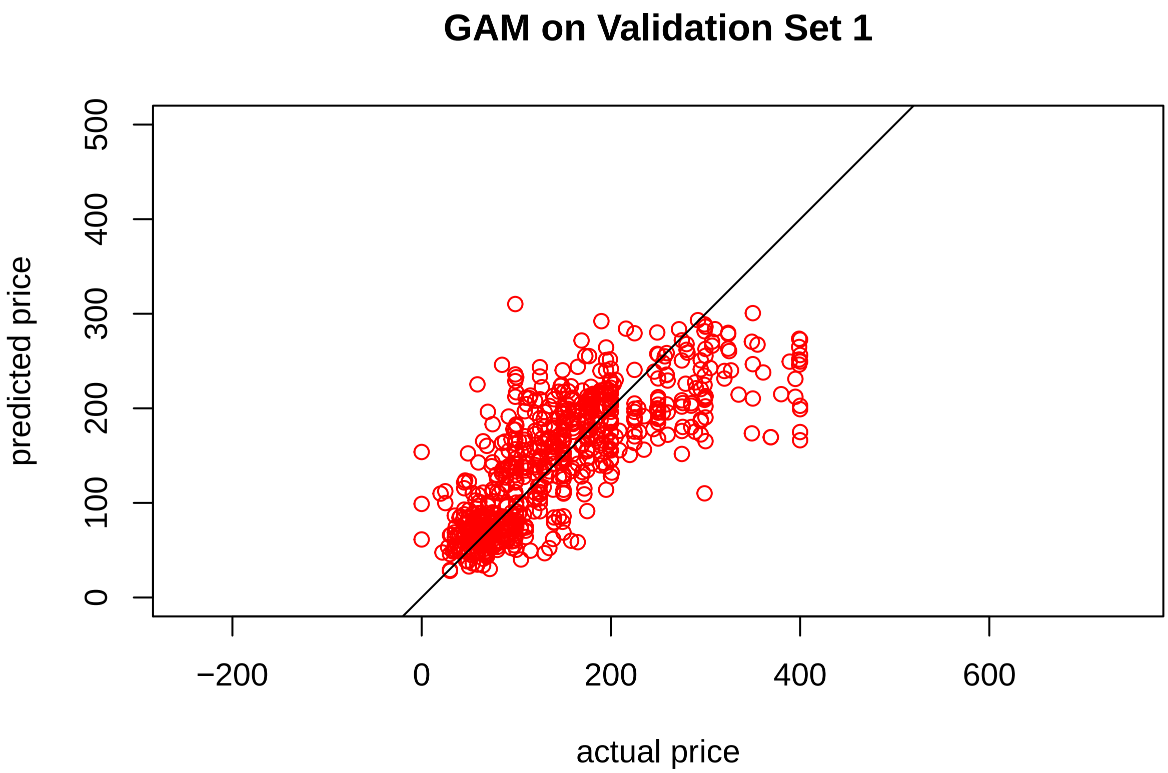
Results of the best model on validation_1 datasets

```
gam.best <- gam.neighborhood
gam.best.v1_rmse <- rmse(boston.data.validation_1, gam.best)
gam.best.v1_rmse # 55.43666
```

```
## [1] 55.43666
```

```
# Most important predictors:
# Parametric: neighborhood, property_type, room_type, instant_bookable
# Non-parametric: accommodates, bedrooms, guests_included
```

```
plot_predicts_gam(boston.data.validation_1, gam.best, "GAM on Validation Set 1", "red")
```



Regression Trees

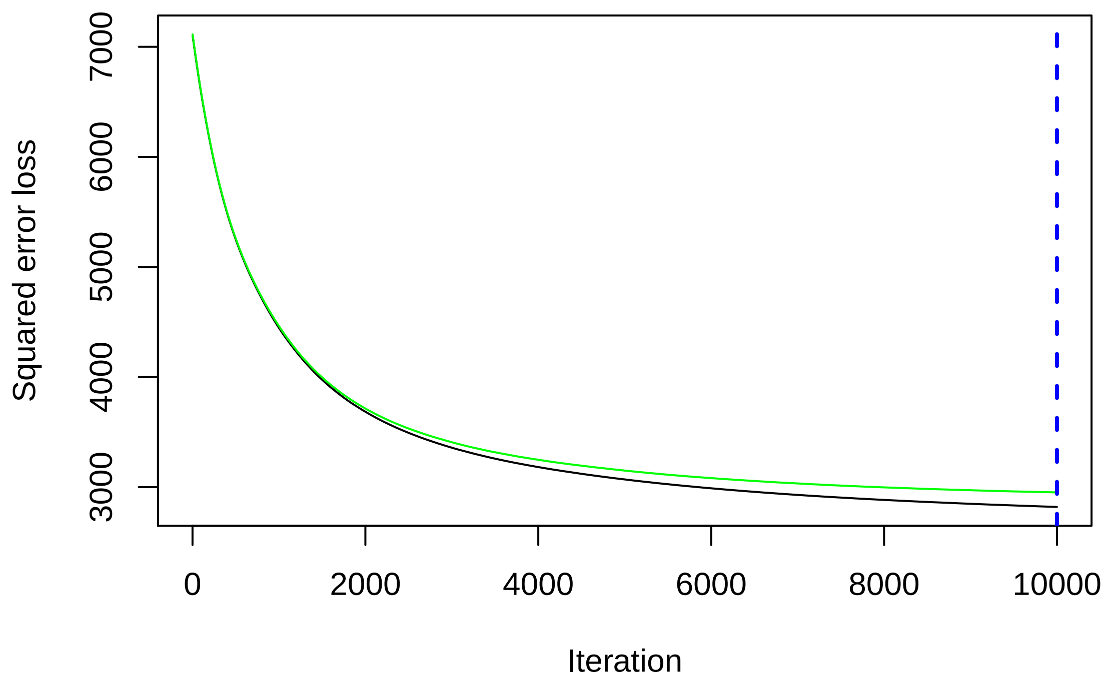
Train each of the transformations

```
boston.data.boost <- gbm(price ~ ., boston.data.training, distribution="gaussian", n.trees=10000, cv.fol
boston.dboth.boost <- gbm(price ~ ., boston.dboth.training, distribution="gaussian", n.trees=10000, cv.
boston.ddowntown.boost <- gbm(price ~ ., boston.ddowntown.training, distribution="gaussian", n.trees=100
boston.dairport.boost <- gbm(price ~ ., boston.dairport.training, distribution="gaussian", n.trees=1000
```

Results of neighborhoods

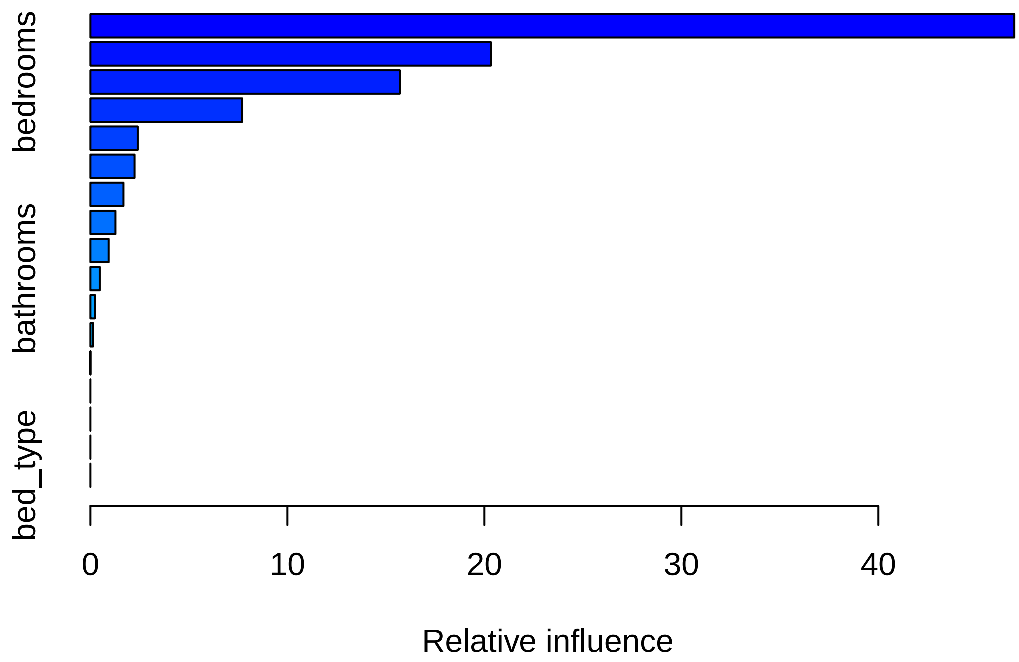
```r
gbm.perf(boston.data.boost)
```

```
## Using cv method...
```



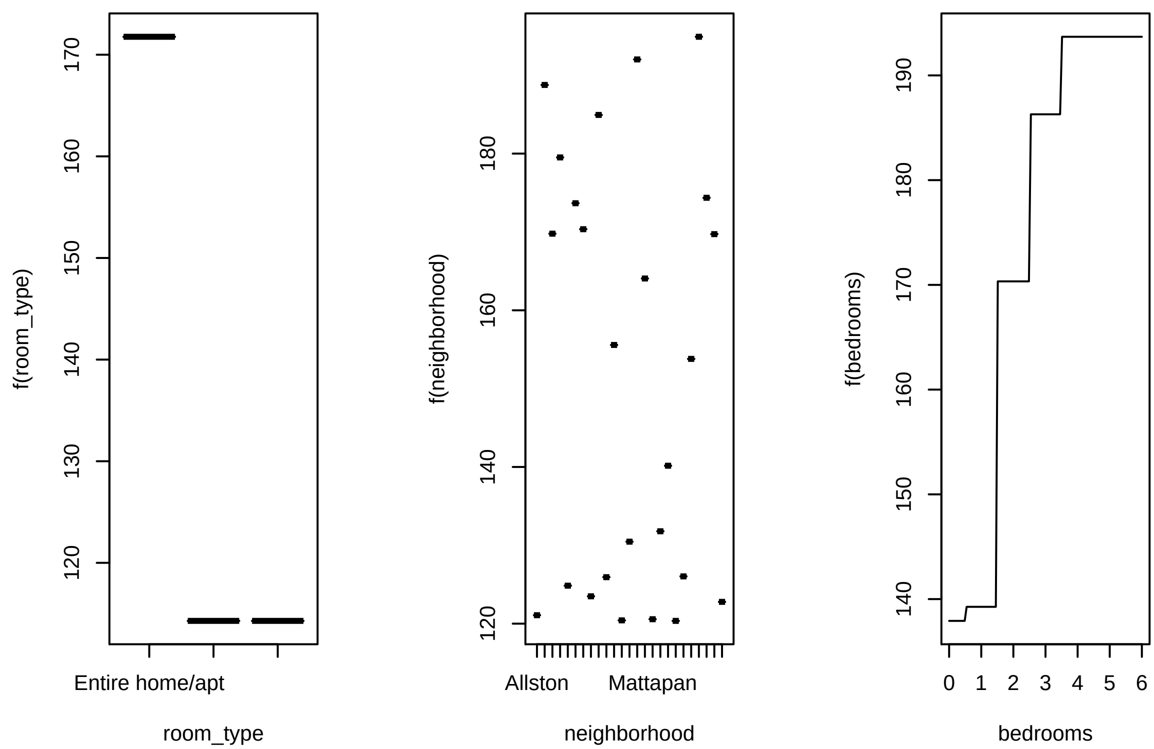

```
## [1] 10000
```

```r
summary(boston.data.boost)
```




```
##                                                   var      rel.inf
## room_type                                   room_type 46.902021406
## neighborhood                             neighborhood 20.329109091
## bedrooms                                     bedrooms 15.704864188
## accommodates                             accommodates  7.707761783
## property_type                           property_type  2.402183578
## guests_included                       guests_included  2.240084631
## beds                                             beds  1.677515267
## instant_bookable                     instant_bookable  1.271554395
## cancellation_policy               cancellation_policy  0.924653047
## bathrooms                                   bathrooms  0.472544863
## minimum_nights                         minimum_nights  0.227962547
## number_of_reviews                   number_of_reviews  0.136885338
## is_business_travel_ready is_business_travel_ready  0.002859867
## X                                                   X  0.000000000
## host_is_superhost                   host_is_superhost  0.000000000
## host_identity_verified         host_identity_verified  0.000000000
## bed_type                                     bed_type  0.000000000
```

```r
par(mfrow=c(1, 3))
plot(boston.data.boost, i=paste(summary(boston.data.boost, plotit=FALSE)$var[[1]], "", sep=""))
plot(boston.data.boost, i=paste(summary(boston.data.boost, plotit=FALSE)$var[[2]], "", sep=""))
plot(boston.data.boost, i=paste(summary(boston.data.boost, plotit=FALSE)$var[[3]], "", sep=""))
```



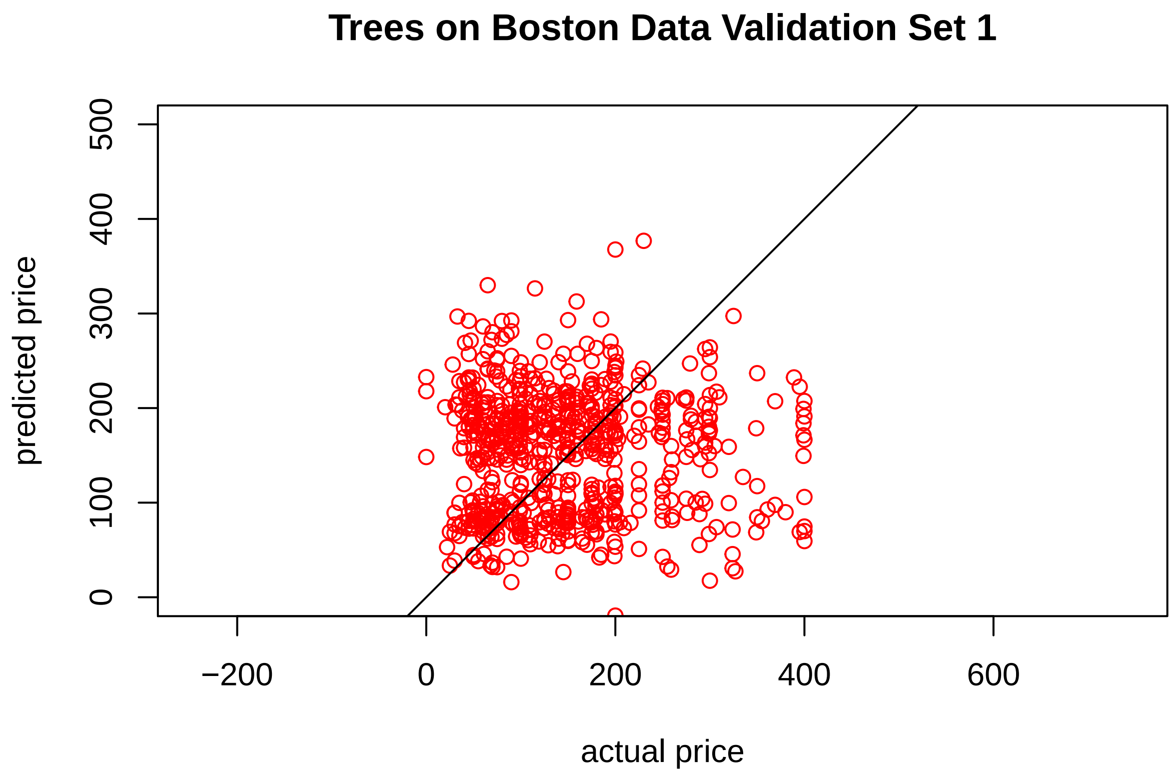

```
yhat <- predict(boston.data.boost, newdata=boston.data.validation_1)
```

```
## Using 10000 trees...
```

```
sqrt(mean((yhat - boston.data.validation_1.test)^2))
```

```
## [1] 55.74535
```

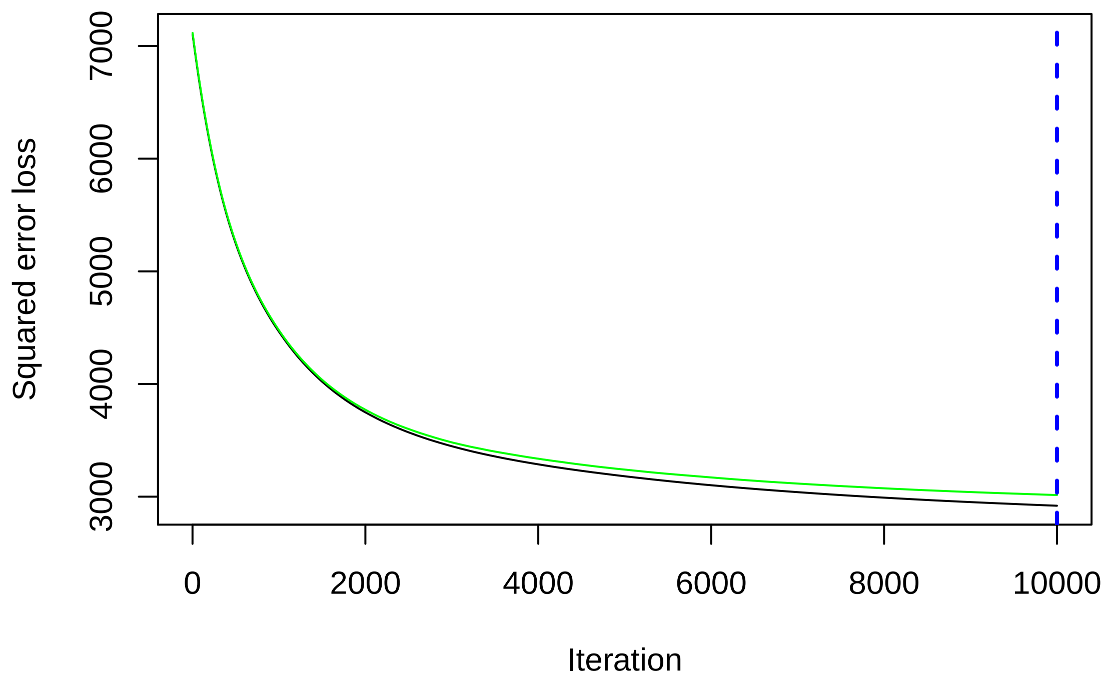
```
plot_predicts(yhat, boston.data.validation_1$price, "Trees on Boston Data Validation Set 1", "red")
```



Results of dboth

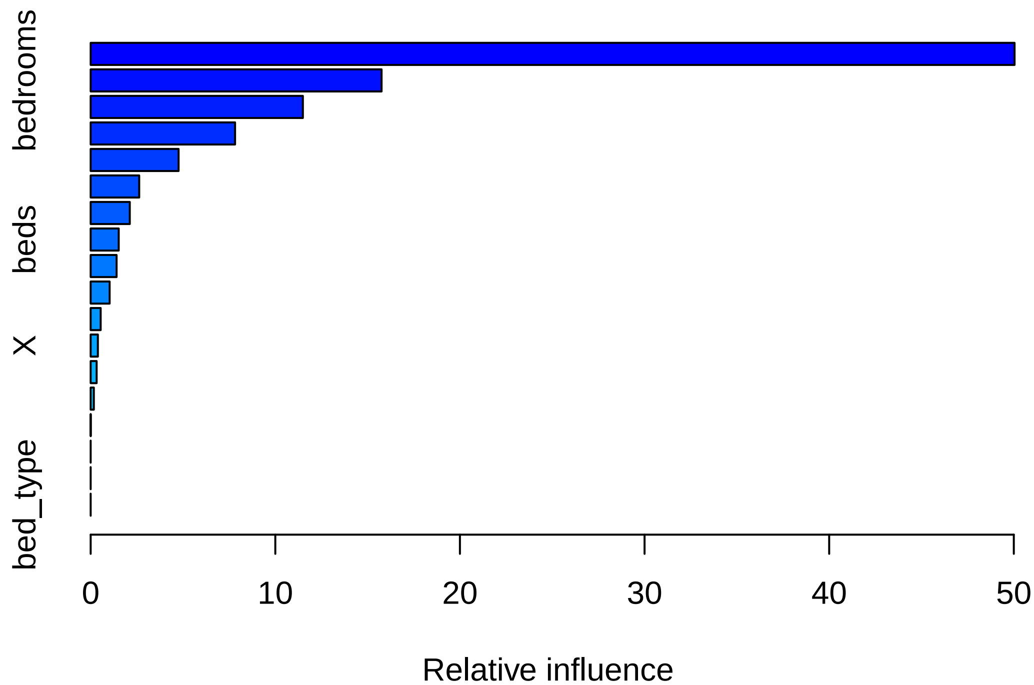
```
gbm.perf(boston.dboth.boost)
```

```
## Using cv method...
```



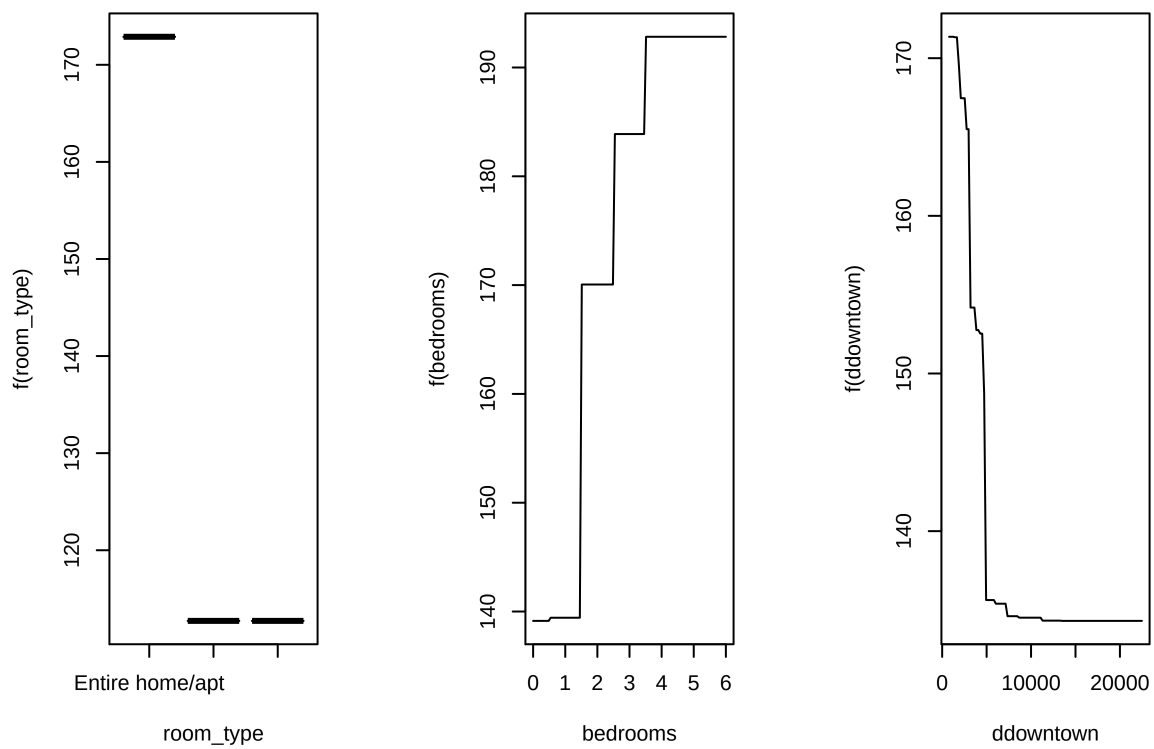

```
## [1] 10000
```

```r
summary(boston.dboth.boost)
```




```
##                                                  var     rel.inf
## room_type                                  room_type 50.04056656
## bedrooms                                    bedrooms 15.75653067
## ddowntown                                  ddowntown 11.49398791
## accommodates                            accommodates  7.82123675
## dairport                                    dairport  4.76219213
## property_type                          property_type  2.62872238
## guests_included                      guests_included  2.11881030
## beds                                            beds  1.51953974
## instant_bookable                    instant_bookable  1.40348664
## cancellation_policy              cancellation_policy  1.02669766
## bathrooms                                  bathrooms  0.54091294
## X                                                  X  0.38991469
## number_of_reviews                  number_of_reviews  0.32350215
## minimum_nights                        minimum_nights  0.17139534
## is_business_travel_ready is_business_travel_ready  0.00250415
## host_is_superhost                  host_is_superhost  0.00000000
## host_identity_verified        host_identity_verified  0.00000000
## bed_type                                    bed_type  0.00000000
```

```
par(mfrow=c(1, 3))
plot(boston.dboth.boost, i=paste(summary(boston.dboth.boost, plotit=FALSE)$var[[1]], "", sep=""))
plot(boston.dboth.boost, i=paste(summary(boston.dboth.boost, plotit=FALSE)$var[[2]], "", sep=""))
plot(boston.dboth.boost, i=paste(summary(boston.dboth.boost, plotit=FALSE)$var[[3]], "", sep=""))
```



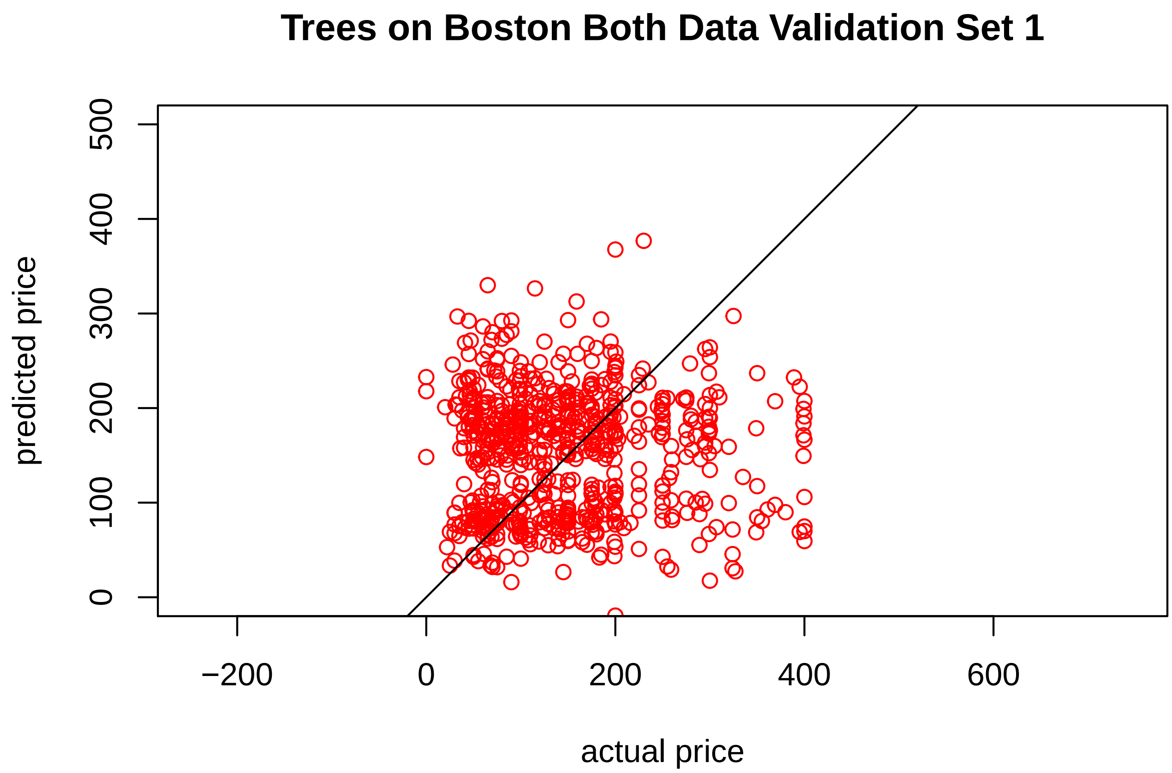

```
yhat <- predict(boston.dboth.boost, newdata=boston.dboth.validation_1)
```

```
## Using 10000 trees...
```

```
sqrt(mean((yhat - boston.dboth.validation_1.test)^2))
```

```
## [1] 56.552
```

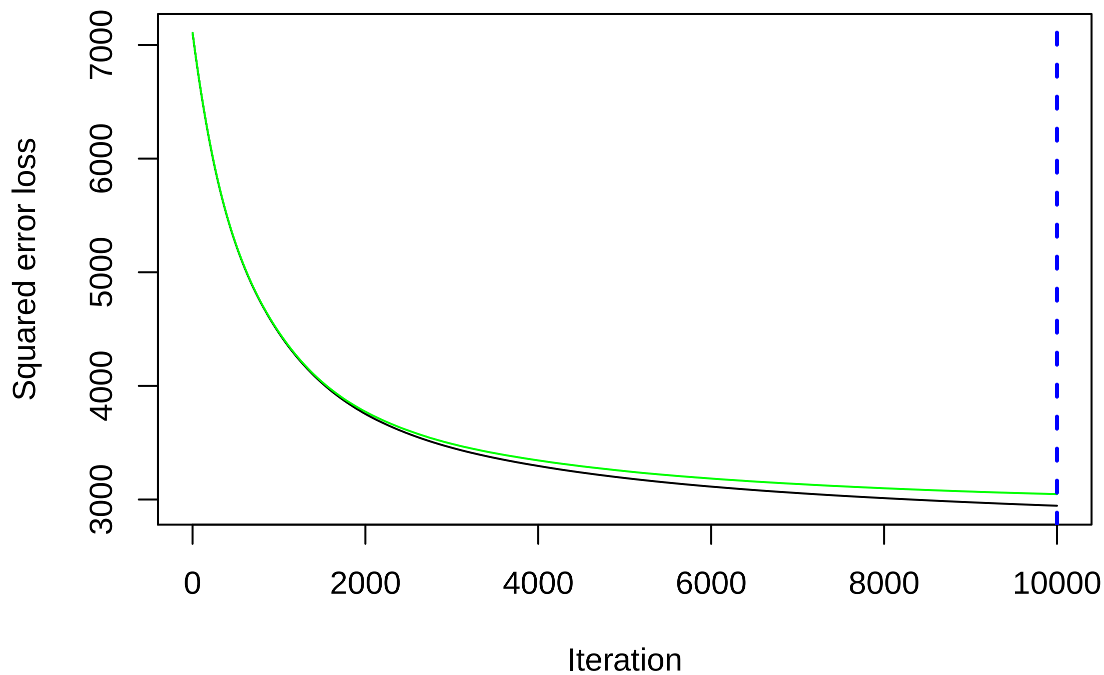
```
plot_predicts(yhat, boston.dboth.validation_1$price, "Trees on Boston Both Data Validation Set 1", "red
```



Results of ddowntown

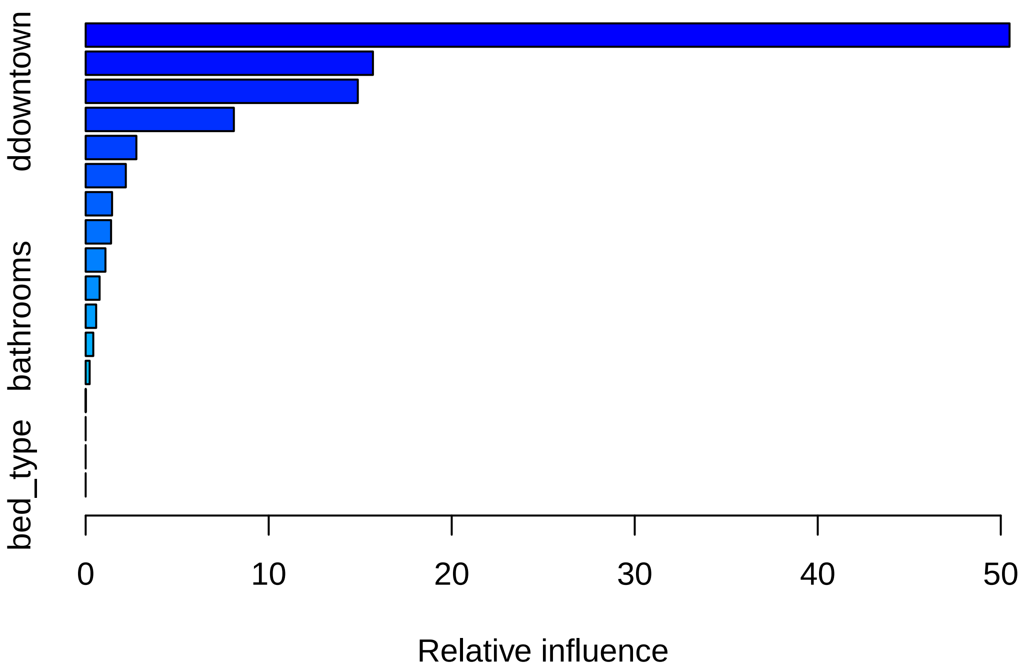
```
gbm.perf(boston.ddowntown.boost)
```

```
## Using cv method...
```



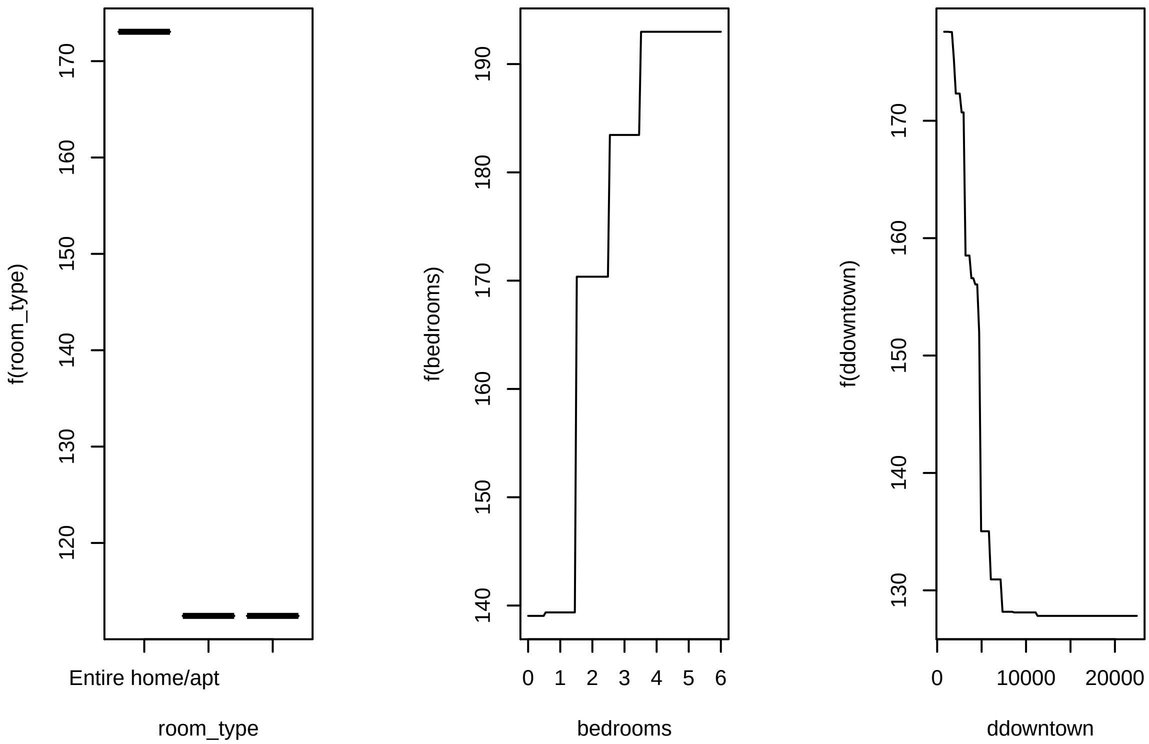

```
## [1] 10000
```

```r
summary(boston.ddowntown.boost)
```




```
##                                                 var      rel.inf
## room_type                                 room_type 50.479988132
## bedrooms                                   bedrooms 15.695991149
## ddowntown                                 ddowntown 14.870256667
## accommodates                           accommodates  8.097831270
## property_type                         property_type  2.771372775
## guests_included                     guests_included  2.194769180
## instant_bookable                   instant_bookable  1.444161661
## beds                                           beds  1.387947725
## cancellation_policy             cancellation_policy  1.081001274
## X                                                 X  0.762394147
## bathrooms                                 bathrooms  0.573571076
## number_of_reviews                 number_of_reviews  0.416098167
## minimum_nights                       minimum_nights  0.218198543
## is_business_travel_ready is_business_travel_ready  0.006418234
## host_is_superhost                 host_is_superhost  0.000000000
## host_identity_verified       host_identity_verified  0.000000000
## bed_type                                   bed_type  0.000000000
```

```
par(mfrow=c(1, 3))
plot(boston.ddowntown.boost, i=paste(summary(boston.ddowntown.boost, plotit=FALSE)$var[[1]], "", sep="")
plot(boston.ddowntown.boost, i=paste(summary(boston.ddowntown.boost, plotit=FALSE)$var[[2]], "", sep="")
plot(boston.ddowntown.boost, i=paste(summary(boston.ddowntown.boost, plotit=FALSE)$var[[3]], "", sep="")
```



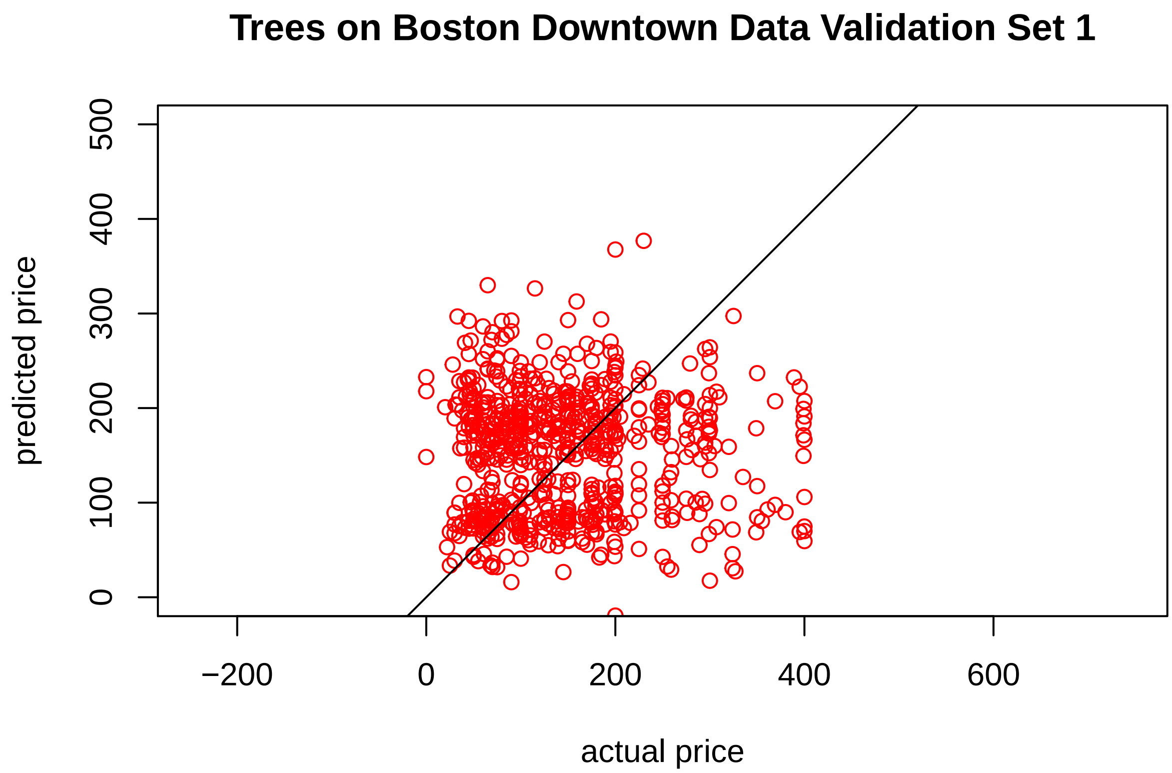

```r
yhat <- predict(boston.ddowntown.boost, newdata=boston.ddowntown.validation_1)
```

```
## Using 10000 trees...
```

```r
sqrt(mean((yhat - boston.ddowntown.validation_1.test)^2))
```

```
## [1] 56.95934
```

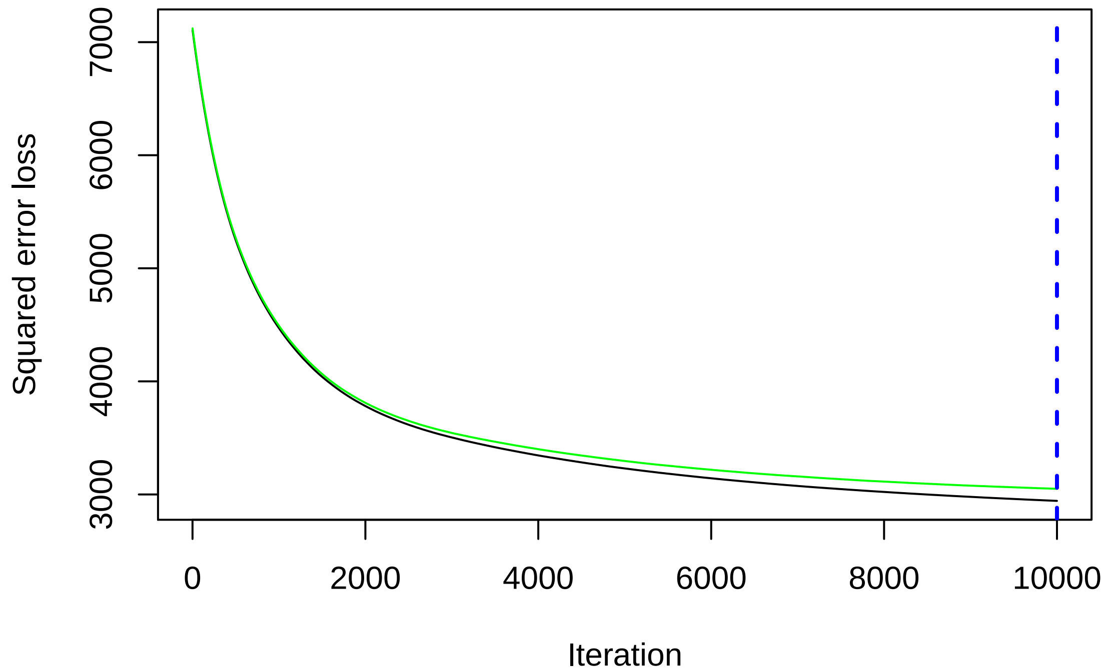
```r
plot_predicts(yhat, boston.ddowntown.validation_1$price, "Trees on Boston Downtown Data Validation Set 
```



Results of dairport

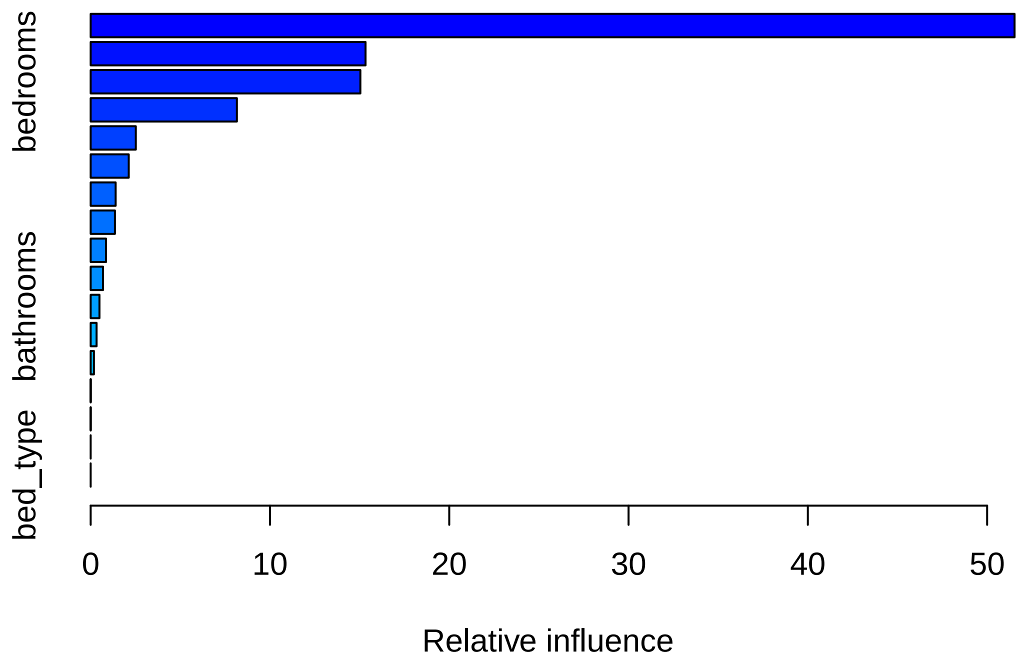
```
gbm.perf(boston.dairport.boost)
```

```
## Using cv method...
```



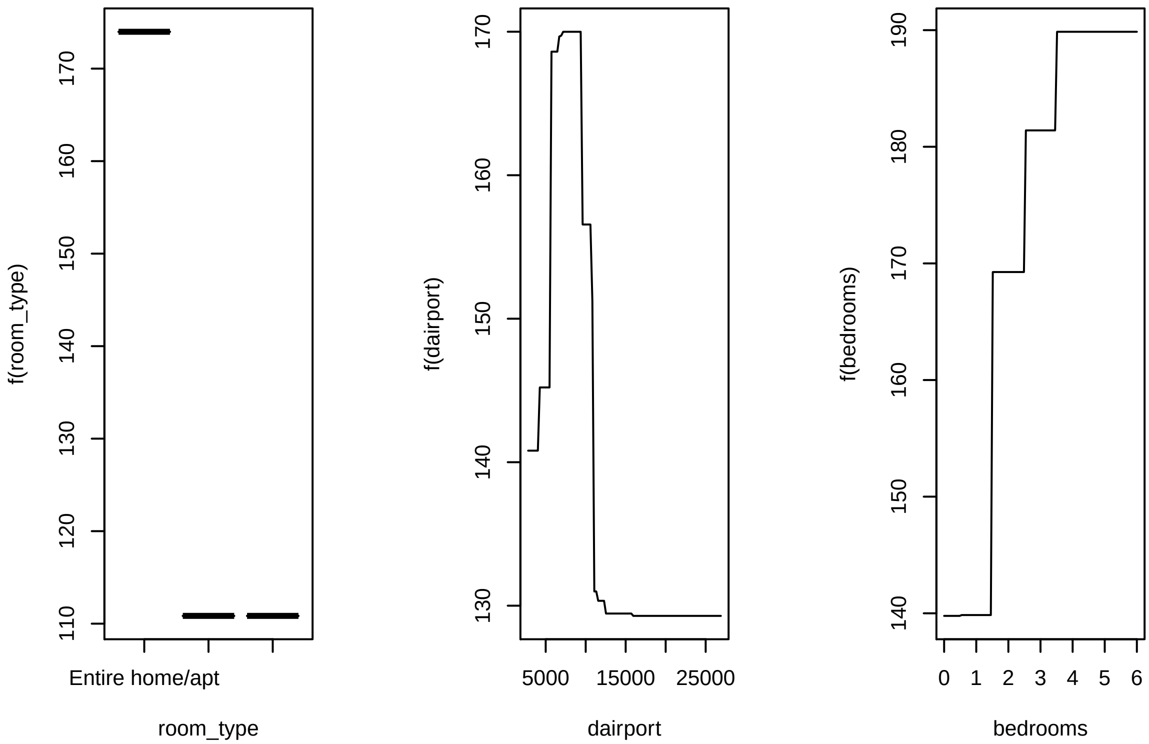

```
## [1] 10000
```

```r
summary(boston.dairport.boost)
```

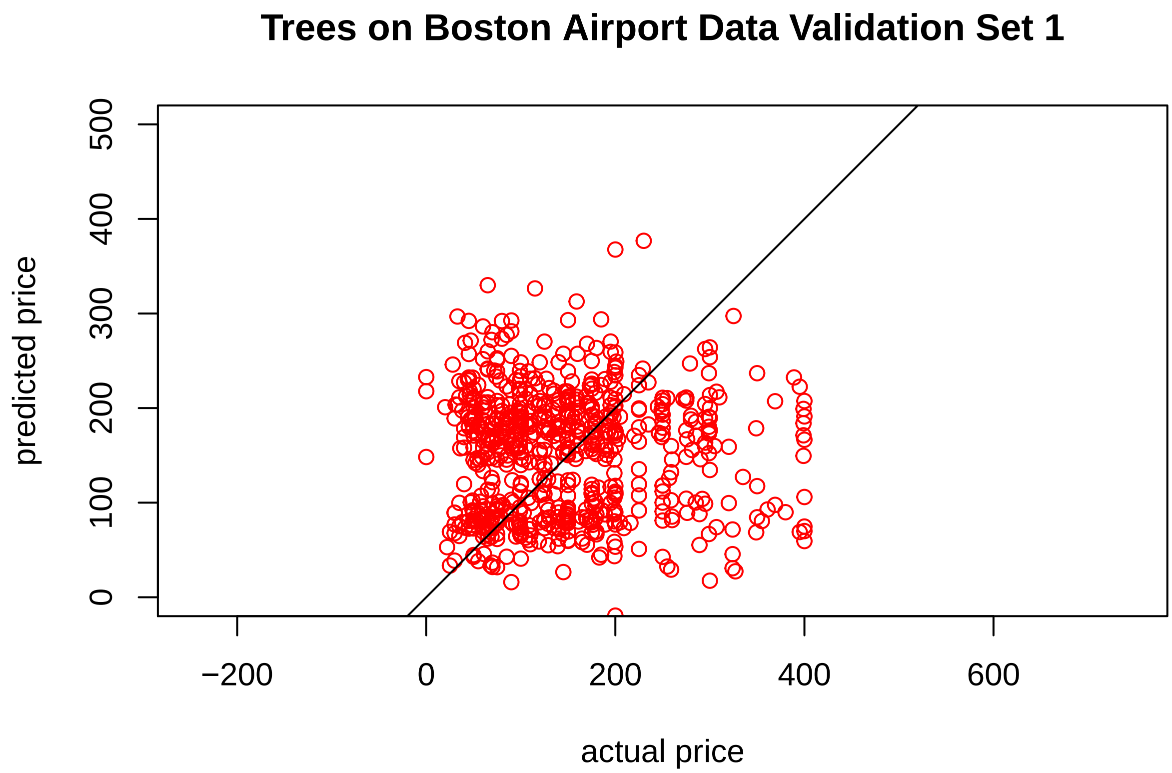



```
##                                                 var      rel.inf
## room_type                                 room_type 51.529190299
## dairport                                   dairport 15.331317302
## bedrooms                                   bedrooms 15.042769665
## accommodates                           accommodates  8.155057630
## property_type                         property_type  2.518724816
## guests_included                     guests_included  2.123554144
## beds                                           beds  1.393094164
## instant_bookable                   instant_bookable  1.353913000
## cancellation_policy             cancellation_policy  0.857509865
## X                                                 X  0.689249892
## bathrooms                                 bathrooms  0.490492202
## number_of_reviews                 number_of_reviews  0.330708392
## minimum_nights                       minimum_nights  0.180950593
## is_business_travel_ready is_business_travel_ready  0.002538401
## host_identity_verified       host_identity_verified  0.000929635
## host_is_superhost                 host_is_superhost  0.000000000
## bed_type                                   bed_type  0.000000000
```

```r
par(mfrow=c(1, 3))
plot(boston.dairport.boost, i=paste(summary(boston.dairport.boost, plotit=FALSE)$var[[1]], "", sep=""))
plot(boston.dairport.boost, i=paste(summary(boston.dairport.boost, plotit=FALSE)$var[[2]], "", sep=""))
plot(boston.dairport.boost, i=paste(summary(boston.dairport.boost, plotit=FALSE)$var[[3]], "", sep=""))
```




```
yhat <- predict(boston.dairport.boost, newdata=boston.dairport.validation_1)

## Using 10000 trees...

sqrt(mean((yhat - boston.dairport.validation_1.test)^2))

## [1] 56.5845

plot_predicts(yhat, boston.dairport.validation_1$price, "Trees on Boston Airport Data Validation Set 1"
```



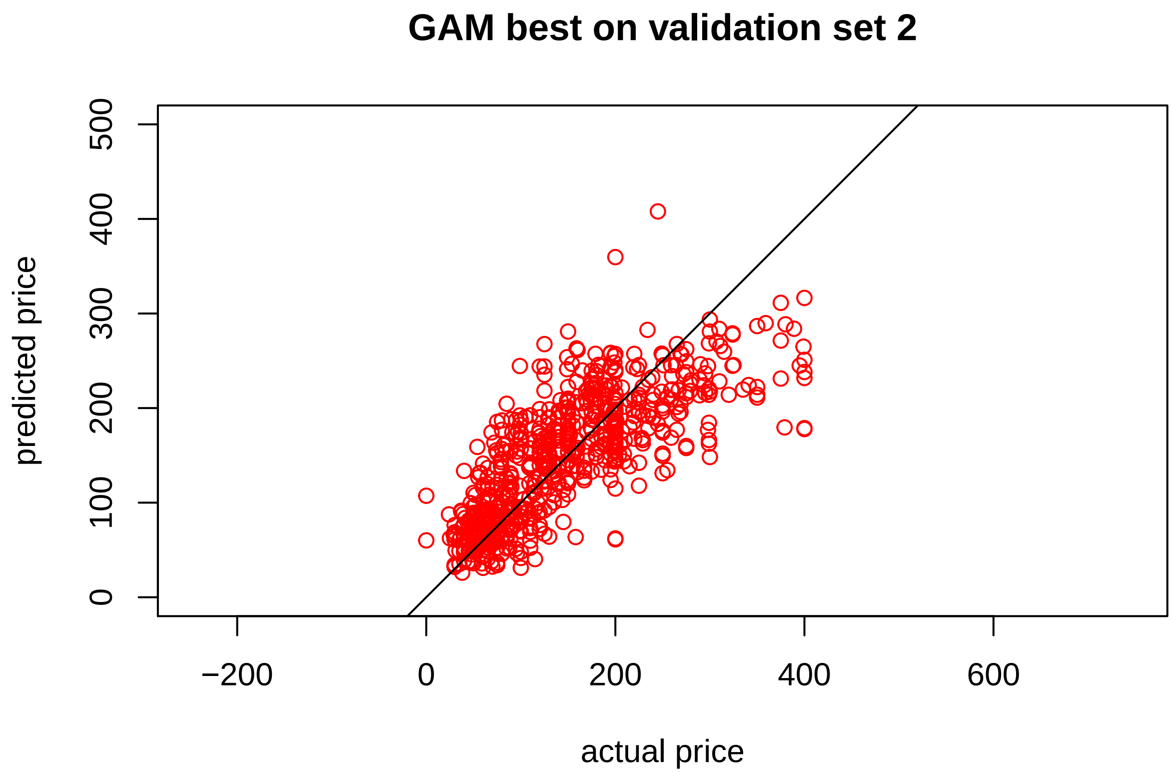
Best Model

Results of the overall best model(GAM - Original dataset) on validation_2 dataset:

```
gam.best.v2_rmse <- rmse(boston.data.validation_2, gam.best)
gam.best.v2_rmse # 52.29939
```

```
## [1] 52.29939
```

```
plot_predicts_gam(boston.data.validation_2, gam.best, "GAM best on validation set 2", "red")
```


GAM best on validation set 2
predicted price
actual price
0
100
200
300
400
500
−200
0
200
400
600