Machine Learning Final Project: Airbnb Pricing

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1 Introduction

Airbnb is a popular online company through which property owners (known as "hosts") can short-term rent their spaces to consumers as an alternative to hotels. A host must decide what daily price to charge for his or her space based on its amenities. Clearly, with data on listed properties, this can be considered as a regression problem for supervised machine learning. However, many real estate datasets include categorical location features with large numbers of levels - which can pose computational difficulties for some methods. With that in mind, in this project we investigate two questions:

(1) To what degree can supervised machine learning techniques be used to assist an Airbnb host in determining an appropriate listing price for their property?

(2) For Airbnb data, can the categorical feature of "neighborhood" be replaced with a continuous feature of driving distance to a geographic point of interest (e.g., an airport) and have comparable results?

To address these questions, we use data collected on Boston Airbnb property listings by the Inside Airbnb project[1]. Our analysis shows that (1) while not outstanding, the performance of the machine learning techniques is useful for an Airbnb host, and (2) replacing the "neighborhood" feature with either driving distance to the Boston airport or to the Boston downtown results in nearly identical performance.

2 Methodology

2.1 Experimental Design

In order to perform our analysis, we conduct the following steps:

(1) Collect Data: For our base data, we use the Airbnb property listing data collected by the Inside Airbnb project for the city of Boston which is available for public download[2]. The data contains 4870 rows and 96 columns.

(2) Select Features: At this point, our data contains 96 features, many of which are textual data that are inappropriate for use in this analysis. After review, we select the following 17 relevant features for consideration:

host_is_superhost (categorical - *YES/NO*) whether the host is an "Airbnb Superhost"

host_identity_verified (categorical - *YES/NO*) whether Airbnb has verified the identity of the host

neighborhood (categorical - *25 levels*) the neighborhood that the property is in

property_type (categorical - *17 levels*) the type of property

room_type (categorical - *Entire home/Private room/Shared room*) the type of room

accommodates (continuous) the number of people the property can hold

bathrooms (continuous) the number of bathrooms the property has

bedrooms (continuous) the number of bedrooms the property has

beds (continuous) the number of beds the property has

bed_type (categorical - *Airbed/Couch/Futon/Pull-out Sofa/Real Bed*) the type of bed

guests_included (continuous) the number of guests allowed

minimum_nights (continuous) the minimum number of nights for a reservation

number_of_reviews (continuous) the number of reviews a property has received

instant_bookable (categorical - *YES/NO*) whether the property can be reserved through the Airbnb instant booking interface

is_business_travel_ready (categorical - *YES/NO*) whether the property is considered "business travel ready"

cancellation_policy (categorical - *flexible/moderate/strict/super_strict_30/super_strict_60*) the strictness of the cancellation policy is

****price**** (continuous) the feature we are regressing on: the daily price of the property in dollars

(3) Handle Missing Values: After selecting which features to consider, there are 14 rows which contain missing values. This is very small relative to the 4870 total rows in the dataset, so we can remove them without concern about the effect that will have on the analysis.

(4) Handle Outliers: In our analysis of the data, we find that there are a number of outliers with listing prices extremely greater than the median. We make the decision to exclude rows with prices above the 95th percentile. This results in the removal of 240 outliers.

(5) Create Data Transformations: We would like to see if we can replace the categorical feature of "neighborhood" with a continuous feature of driving distance to a geographic point of interest. For this project, we create three transformations of the data to investigate:

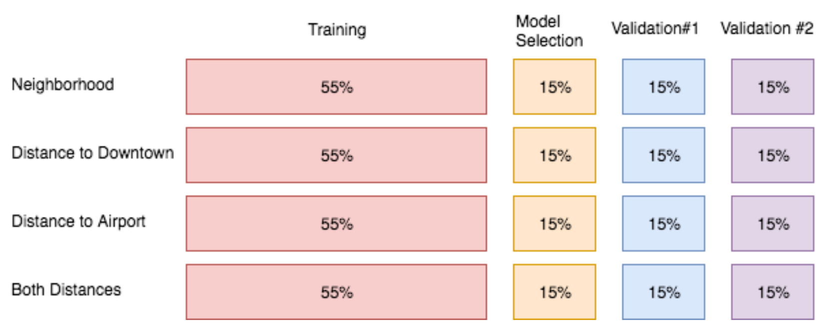
1. "neighborhood" feature replaced with driving distance to Logan International Airport

2. "neighborhood" feature replaced with driving distance to Downtown Crossing Station

3. "neighborhood" feature replaced with both of these.

In order to create these transformations, we use the R package "gmapsdistance" to obtain the driving distance from the neighborhood to the point of interest[3]. Also a set of datasets are created having dummy variables for categorical data, for linear regression.

(6) Separate Training/Model Selection/Validation Datasets: For the supervised machine learning task, we need to separate our data into training, model selection, and validation sets. For each data transformation, we randomly allocate 55% of the rows for training, 15% for model selection, 15% for a first validation set, and 15% for a second validation set (see figure). The allocation is performed such that the rows selected for each dataset are identical for each transformation.



(7) Choose Learning Methods: To investigate our questions, we use and compare the performance of three different supervised machine learning techniques: Linear Regression,Generalized Additive Models (GAMs), and Regression Trees.

(8) Apply Methods: For each method, we apply the technique to each of the data transformations. The methods are trained on the training sets, and the model selection sets are used to select the best model within a method.

(9) Compare Results: The best model of each method/transformation combination is evaluated on validation set #1, and the root of the mean square error is obtained. At this point, we now have enough information to analyze the effects of replacing the "neighborhood" feature with our chosen distance metrics.

(10) Validate best Transformation/Method Combination: The method/transformation combination which has the least mean squared error on validation set #1 is evaluated on validation set #2. This ensures that we have a quality estimate of performance without overfitting, and we can now analyze the extent to which these methods can assist a host in determining the listing price for a property.

2.2 Application of Methods

2.2.1 Linear Regression

All linear regression models are applied on the set of datasets containing dummy variables for categorical variables. We choose to apply both LASSO and RIDGE regularization methods and finally compare their results.Both LASSO and RIDGE regularizes the model by penalizing the fitting of too many variables. LASSO model also allows us to do reduce dimensionality via regularization by shrinking the coefficients of a few variable to 0, which essentially results in those variables having no effect on our model. Thus, reducing dimensionality and increasing interpretability and prediction accuracy. In theory, LASSO should give us a better accuracy in our case.

Both parameters - lambda and number of predictors for both approaches are gathered using cross validation. The results are shared below.

2.2.2 Generalized Additive Models

GAMs provide a framework for extending the linear models explored above by representing each predictor as a non-linear function, while maintaining additivity. This approach was explored to investigate if representing continuous features with more degrees of freedom in combination with discrete features would result in a better results.

Each continuous predictor was represented by a Penalized Cubic regression spline[4]. Smoothness selection was performed my maximum likelihood estimation using Restricted Maximum Likelihood (REML). For variable selection, three methods were performed: Regression Subset Selection and Forward Selection on a linear model with all predictors, and a shrinkage method within the GAM itself[5]. The third method produced the best results on the model selection dataset. Essentially, there are smoothness penalties for each predictor, which include a small shrinkage component, so that for large enough smoothing parameters the smooth becomes identically zero.

2.2.3 Regression Trees

When using tree-based methods, there are choices to be made for the tradeoff between interpretability and performance. Specifically, traditional regression trees have highly interpretable results whereas random forest and boosting methods trade interpretability for better performance. For our purposes, interpretability has relatively low importance, as (1) hosts will not change the features of their properties (e.g., changing the number of bedrooms), and (2) comparing data transformations involves comparing only the end results. Therefore, we choose to use boosting trees in our analysis.

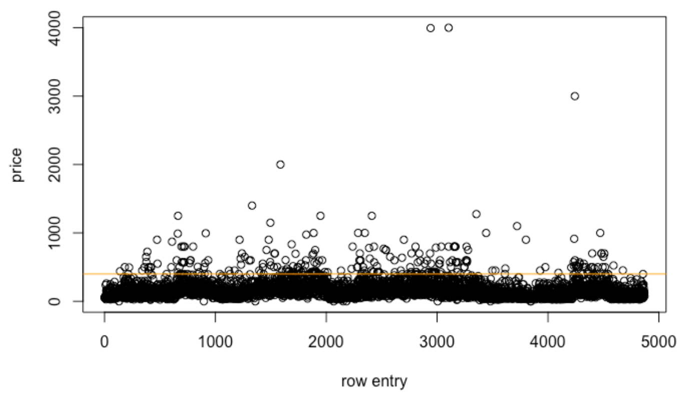
For the parameters of our boosting trees, we select a tree depth of 1 and $\lambda = 0.001$. The number of trees is selected with cross-validation with a result of 10,000 trees.

3 Results

3.1 Intermediate Results

3.1.1 Data Analysis

The figure below shows the prices of each Airbnb listing before removal of outliers, with the orange line being the 95th percentile we used as the cutoff.



In the table below are statistics for price after removing outliers.

Min	1st Qu.	Median	Mean	3rd Qu.	Max	Standard Deviation
\$0.0	\$80.0	\$133.0	\$ 148.8	\$199.0	\$400.0	\$84.6

3.1.2 Linear Regression

We see that the MSE for LASSO regression were the least for all 4 datasets. However, the dataset containing neighborhood data gave us the best results with Lasso. The results from Model Selection dataset are as below:

Dataset	λ	#Predictors	RMSE(\$)
Neighborhood	0.053	63	56.25
Distance to Downtown	0.16	40	59.17
Distance to Airport	0.21	40	60.42
Both	0.11	41	58.62

3.1.3 GAMs

GAM have the best results on the original dataset with ‘neighborhood‘ as a predictor. Evaluation was performed on the model selection dataset as shown in the table below. The square root of the mean-squared error obtained on the validation set #1 was 55.75. The most significant predictors of ‘price‘ were: ‘neighborhood‘, ‘property_type‘, ‘room_type‘, ‘instant_bookable‘, ‘accommodates‘, ‘bedrooms‘, ‘guests_included‘.’

Dataset	RMSE($)
Neighborhood	55.15
Distance to Downtown	58.05
Distance to Airport	56.24
Both	55.77

3.1.4 Regression Trees

The relative importance of the four most important variables for each transformation are shown in the table below.

	NVar	NRel	DDVar	DDRel	DAVar	DARel	DBVar	DBRel
First	room_type	46.9	room_type	50.6	room_type	51.7	room_type	50.1
Second	neighborhood	20.3	bedrooms	15.7	dairport	15.7	bedrooms	15.8
Third	bedrooms	15.7	ddowntown	15.1	bedrooms	15.1	ddowntown	11.5
Fourth	accommodates	7.7	accommodates	8.1	accommodates	8.2	accommodates	7.9

3.2 Final Results

The square root of the mean squared error of each transformation/method combination on validation set #1 is shown in the figure below.

Table 1: Square Root of the MSE

	Linear Regression	GAM	Regression Trees
Neighborhood	56.82	55.15	55.75
Distance to Downtown	58.95	58.05	57.00
Distance to Airport	60.76	56.24	56.57
Both Distances	58.16	55.77	56.54

The transformation/method combination with the best performance was the dataset with the "neighborhood" feature using the GAM method. This transformation/method combination was tested on validation set #2, and the square root of the mean squared error was 52.30.

4 Discussion

4.1 Answers to Project Questions

(1) Performance

The root of the mean squared error of our best model/transformation combination was $\tilde{5}0$. Considering that the median price is $133 with a standard deviation of $84 , this result is useful but not exceptional. These methods can be used to give an Airbnb host a rough estimate of the price to charge, but it is clear that there is important information not captured by the features we used.

(2) Data Transformation Feasibility

The performance results after replacing the “neighborhood” feature with driving distance to a geographic point of interest were nearly identical to the performance results on the original data. This result raises the concern that the “neighborhood” feature is actually non-informative, and thus transforming it will not have an impact. However, we see in our intermediate analysis that the “neighborhood” and transformed features are consistently in the most influential features as reported by the methods used. Therefore the transformation of the “neighborhood” feature is nontrivial, and our results are evidence that the information captured by this feature can be reasonably represented as distance to some location of importance.

4.2 Improvements and Further Research

There are several ways the work presented in this paper could be expanded. In our analysis, we did not utilize any of the textual features in the original dataset, as this would require techniques outside the scope of the course. However, it is likely that the textual features contain useful information for predicting price, and NLP techniques such as sentiment analysis could be used to include these features and increase performance.

Additionally, we selected the geographic points of interest using our intuition regarding what locations would be relevant for pricing. A more sophisticated process could be developed for selecting points of interest to consider.

5 References

(1) http://insideairbnb.com/about.html

(2) http://insideairbnb.com/get-the-data.html

(3) https://cran.r-project.org/web/packages/gmapsdistance/gmapsdistance.pdf

(4) https://stat.ethz.ch/R-manual/R-devel/library/mgcv/html/smooth.construct.cr.smooth.spec.html

(5) https://stat.ethz.ch/R-manual/R-devel/library/mgcv/html/gam.selection.html

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("", " ", "NA
  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.string
  boston.ddowntown.dummied <- read.csv("../data/boston_ddowntown_dummied.csv", sep = ",", header=TRUE, n
  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)
```

```
## 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

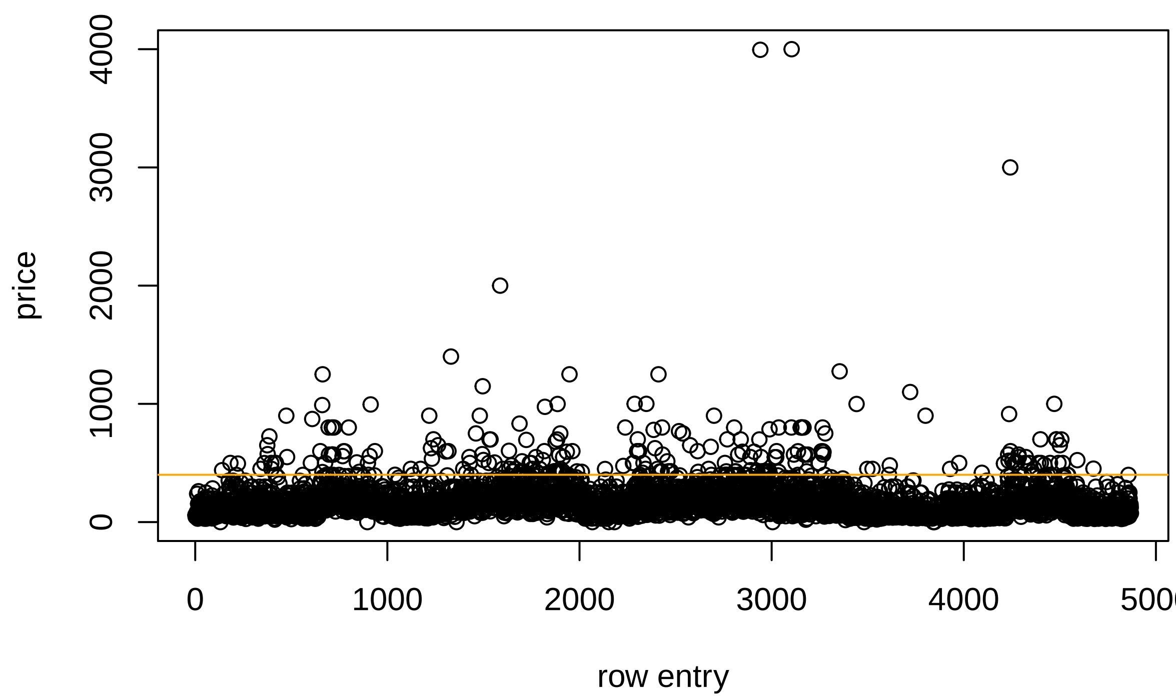
```
# Outlier investigation
summary(boston.data$price)
```

```
##    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")
```

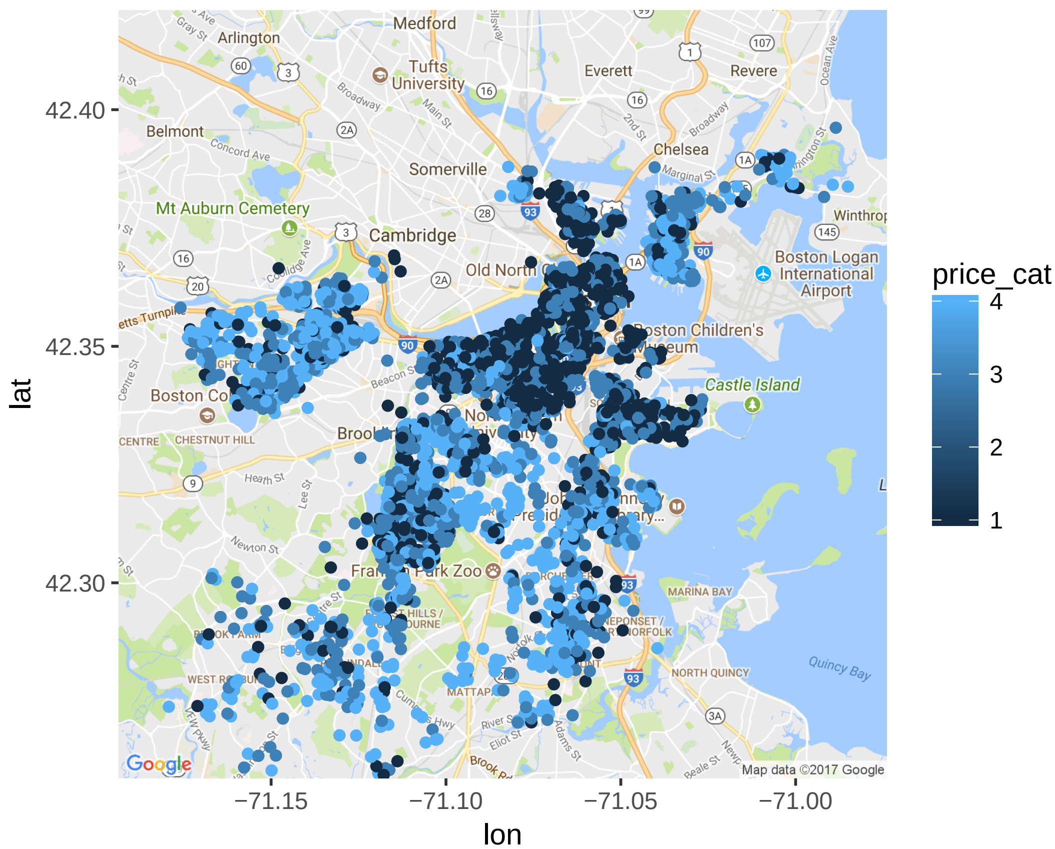



```
# Visualizing the dataset on a map

# 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

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

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

Divide data into training and validation sets

```r
# 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)]
```

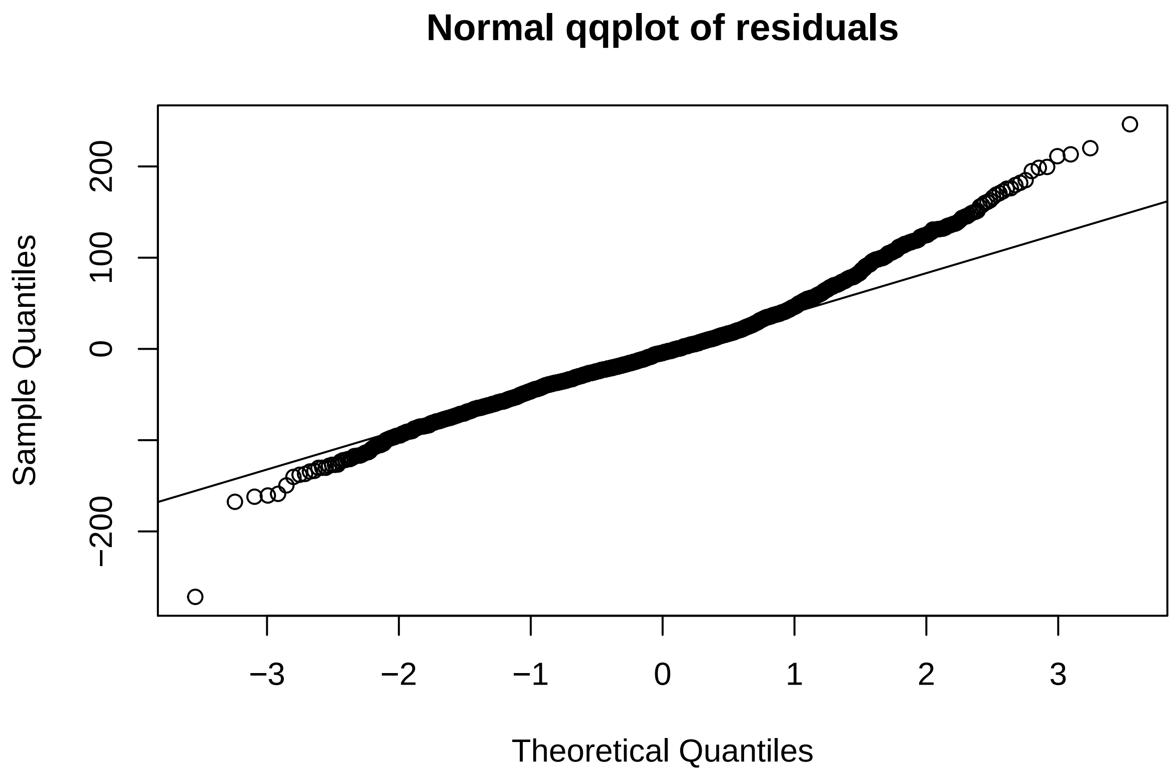
```
# 15% validation #2
validation_2 <- sample(rest, floor(0.15 * num_rows))
rest <- (1:num_rows)[-c(training, model_selection, validation_1, validation_2)]

# 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"]
```

```
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

```
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.

```
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 ) " "                              " "
```

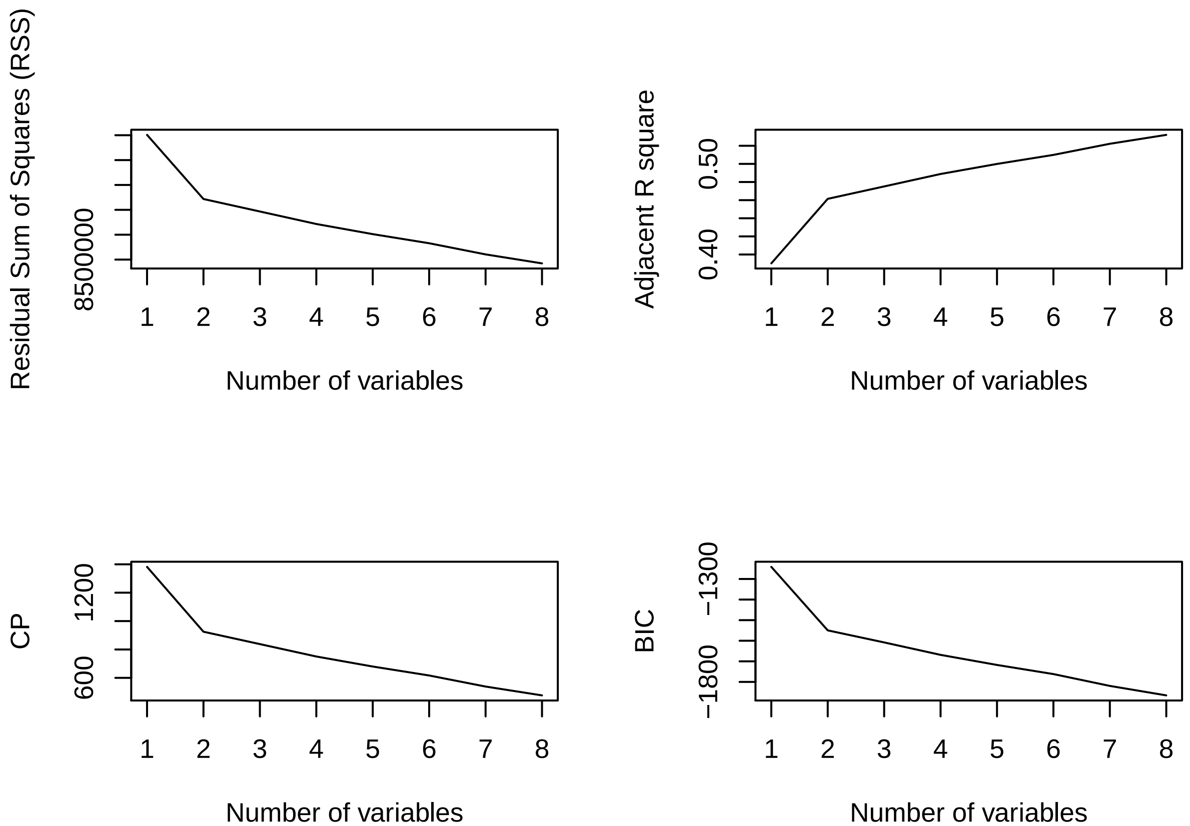
```
## 5  ( 1 ) " "                              " "
## 6  ( 1 ) " "                              " "
## 7  ( 1 ) " "                              " "
## 8  ( 1 ) " "                              " "
##          property_type.Townhouse property_type.Villa
## 1  ( 1 ) " "                     " "
## 2  ( 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)
```

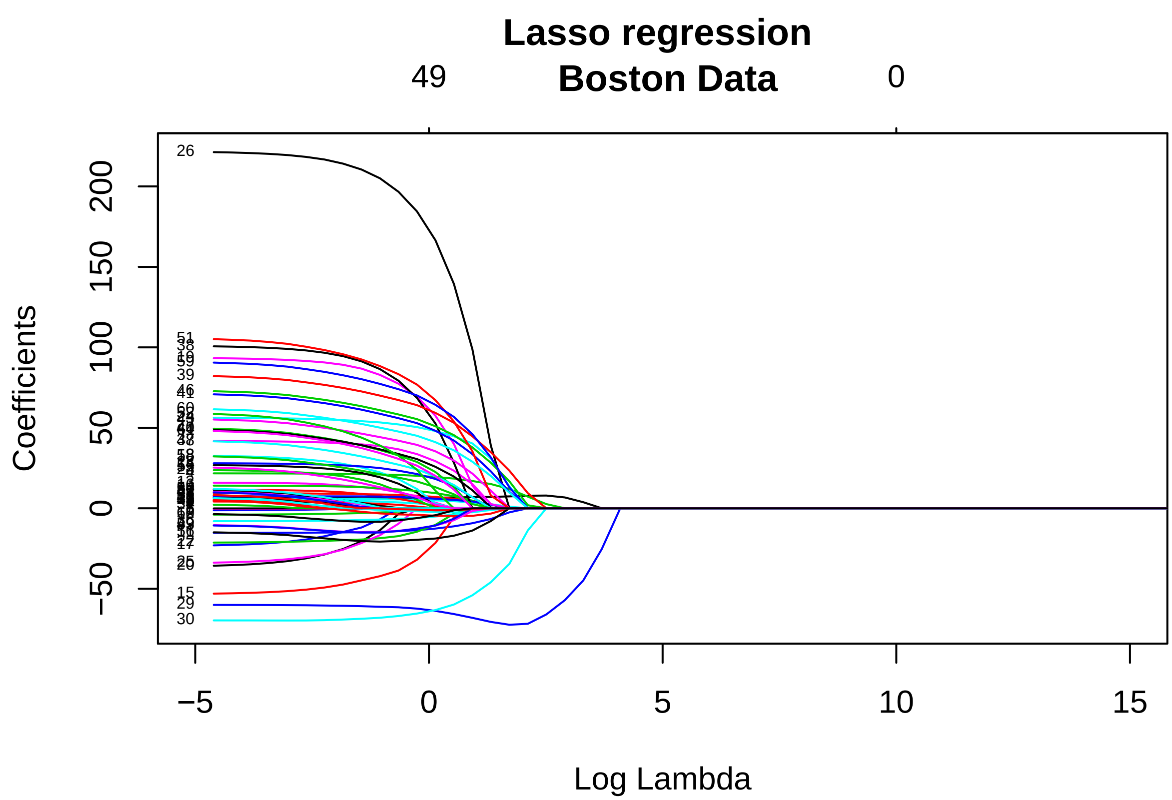
```
##                  (Intercept)                  accommodates
##                   105.497182                      8.300836
##                     bedrooms        room_type.Private.room
##                    22.178145                    -66.779191
##        neighborhood.Back.Bay       neighborhood.Beacon.Hill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

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

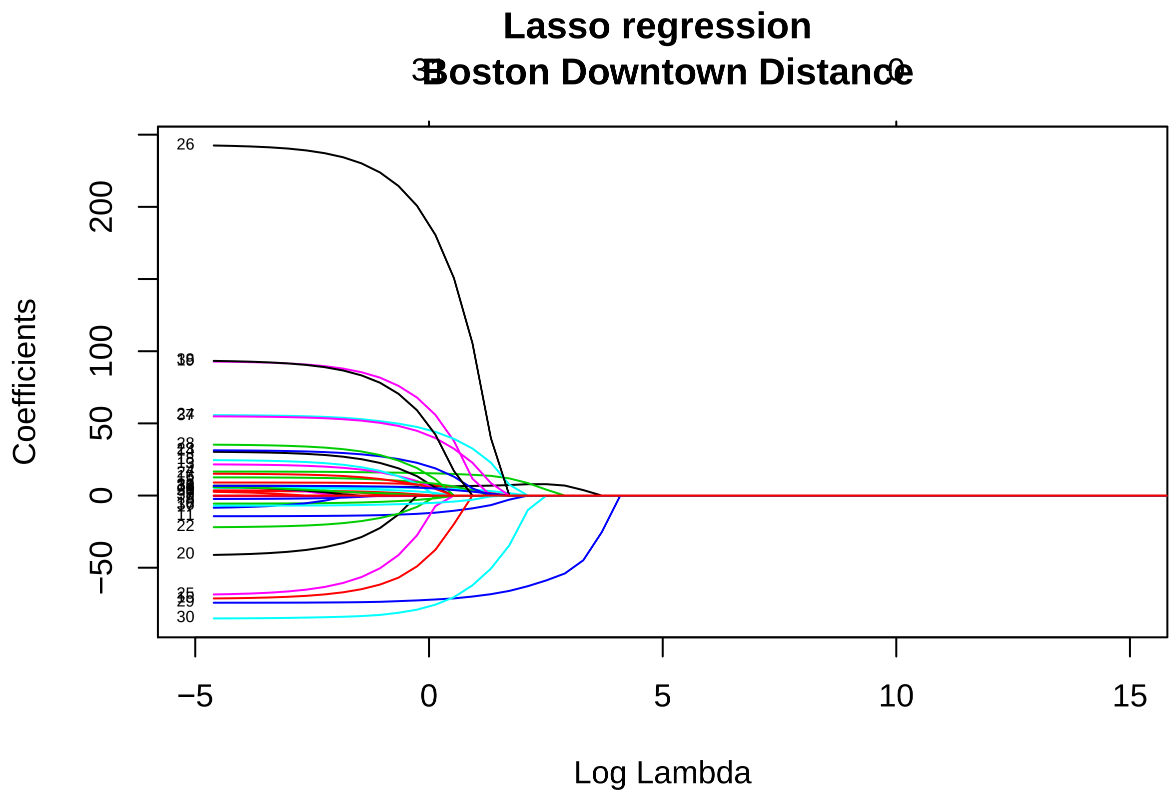
All predictors and Best subset were only used to understand our data better, now to implement linear regression we focus on two majoe approaches - lasso and ridge

Lasso Regression

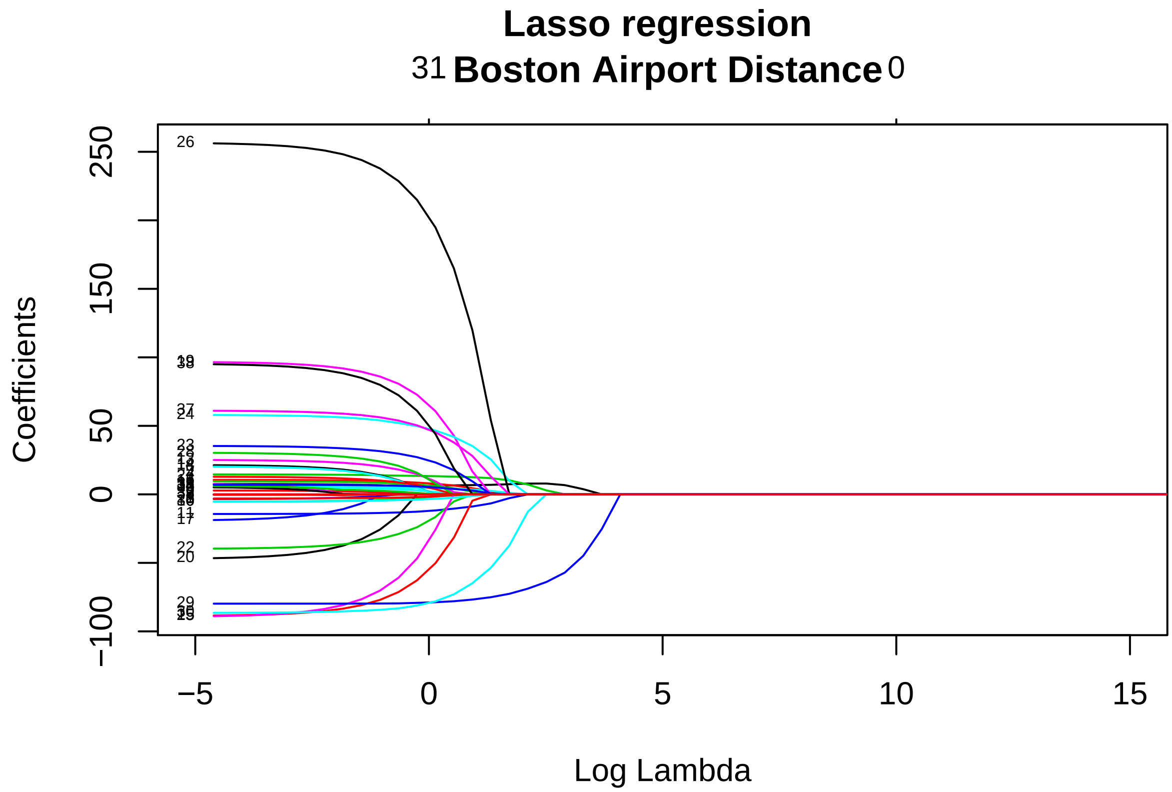
```r
x.boston.data   <- model.matrix(price~.,boston.dummied.training)
x.boston.dboth  <- model.matrix(price~.,boston.dboth.dummied.training)
x.boston.ddowntown  <- model.matrix(price~.,boston.ddowntown.dummied.training)
x.boston.dairport   <- model.matrix(price~.,boston.dairport.dummied.training)

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 =
```



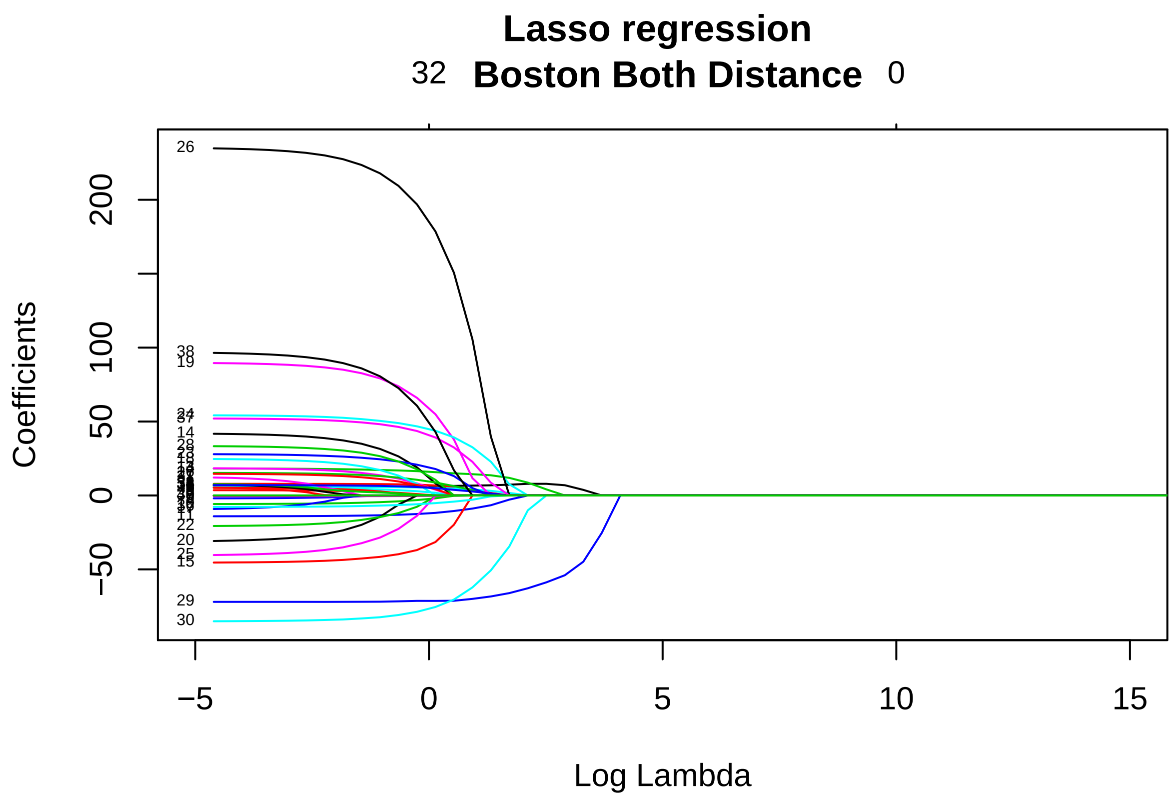

```r
lasso.boston.ddowntown <- glmnet(x.boston.ddowntown,y.boston.ddowntown, alpha = 1, lambda = grid)
plot(lasso.boston.ddowntown, main = "Lasso regression \n Boston Downtown Distance", label = TRUE, xvar =
```



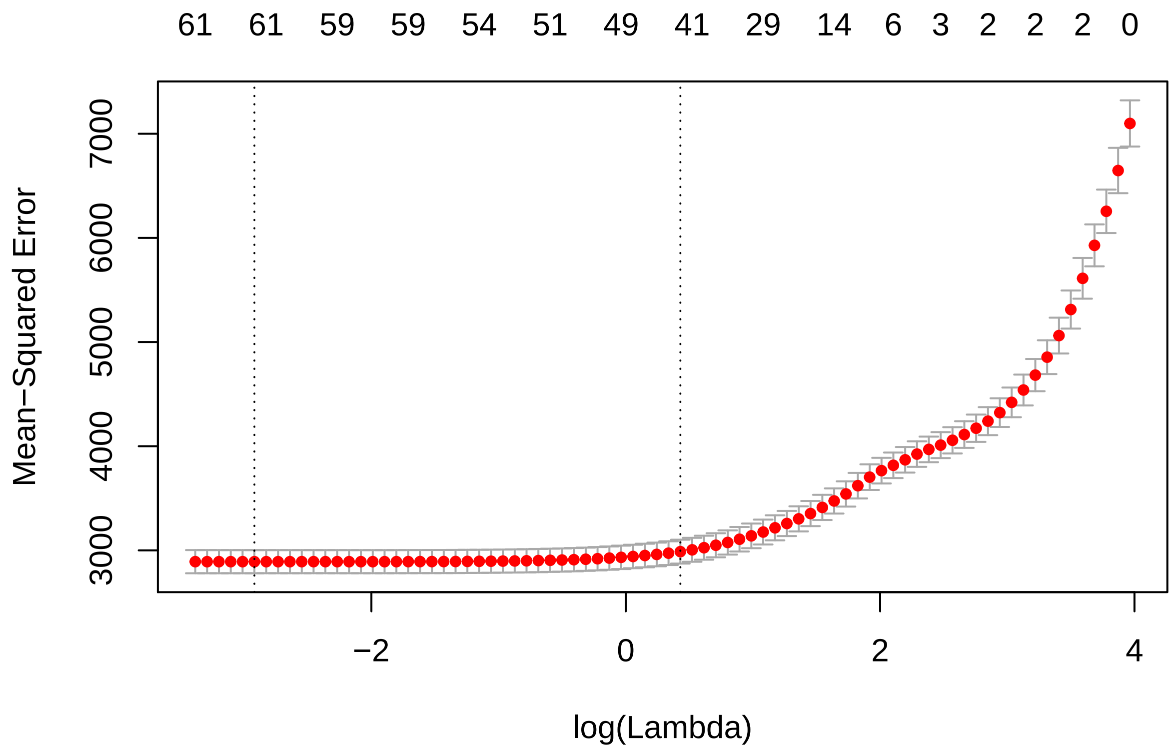

```
lasso.boston.dairport <- glmnet(x.boston.dairport,y.boston.dairport, alpha = 1, lambda = grid)
plot(lasso.boston.dairport, main = "Lasso regression \n Boston Airport Distance", label = TRUE, xvar =
```



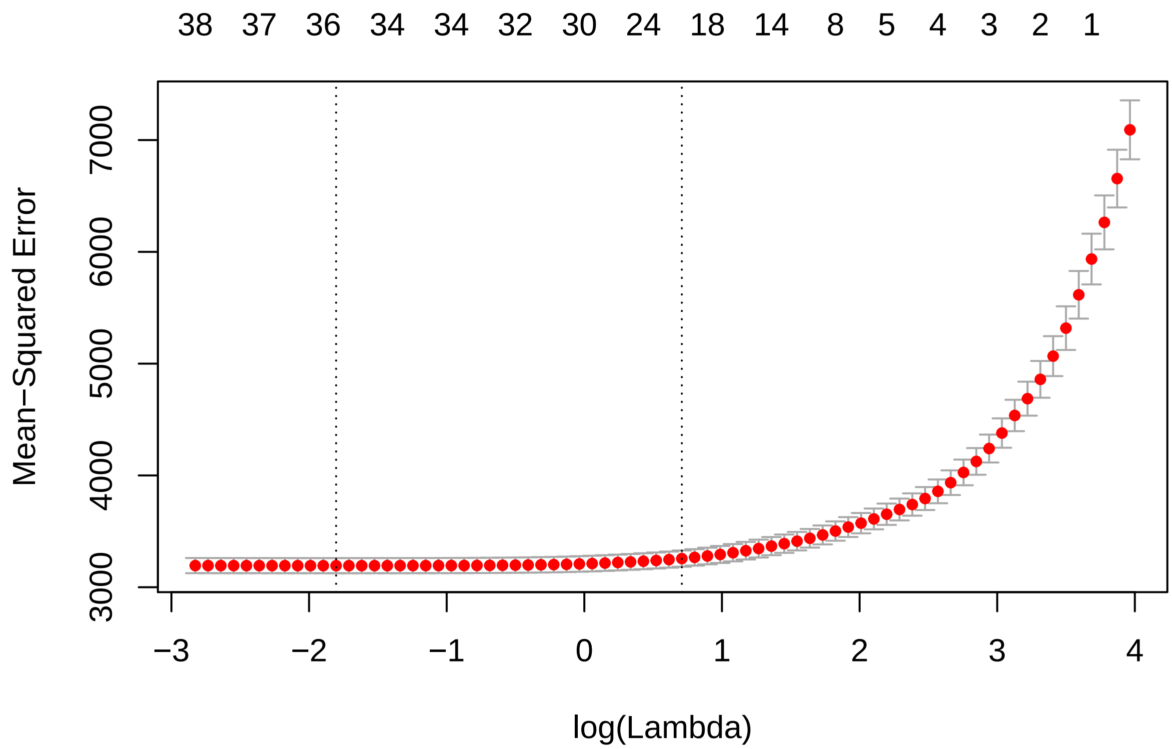

```
lasso.boston.dboth <- glmnet(x.boston.dboth,y.boston.dboth, alpha = 1, lambda = grid)
plot(lasso.boston.dboth, main = "Lasso regression \n Boston Both Distance", label = TRUE, xvar = "lambda
```



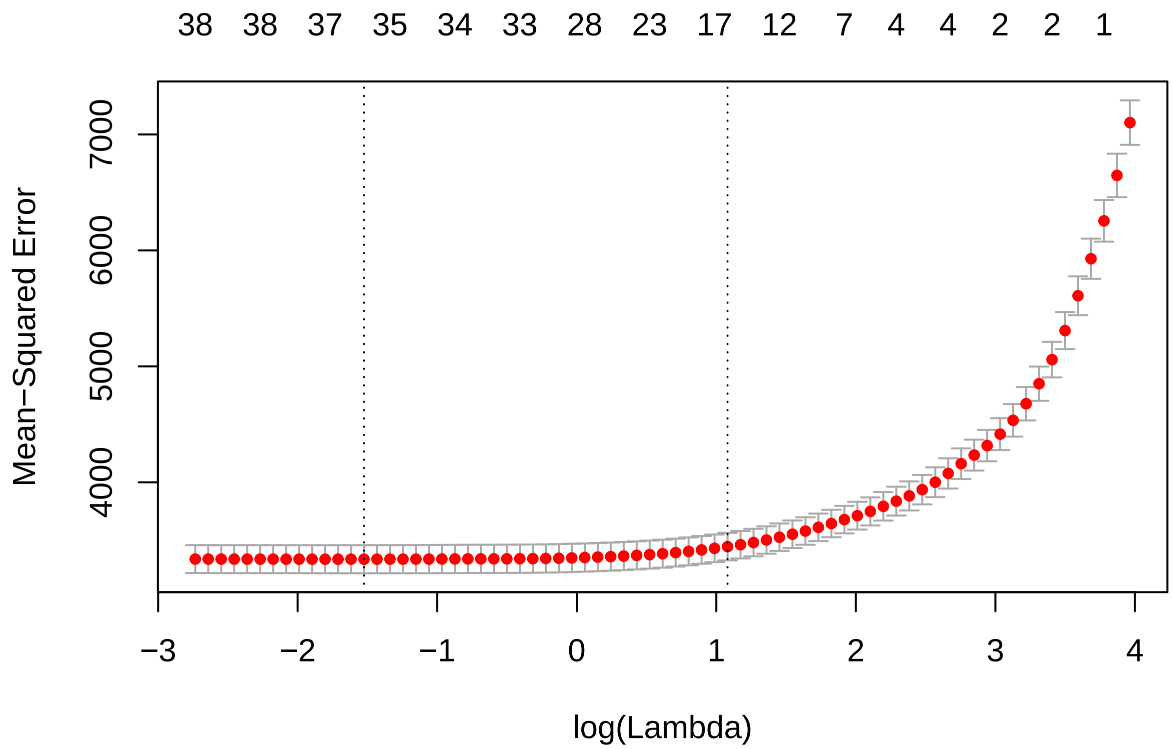

```r
cv.out.data <- cv.glmnet(x.boston.data,y.boston.data,alpha = 1)
plot(cv.out.data)
```



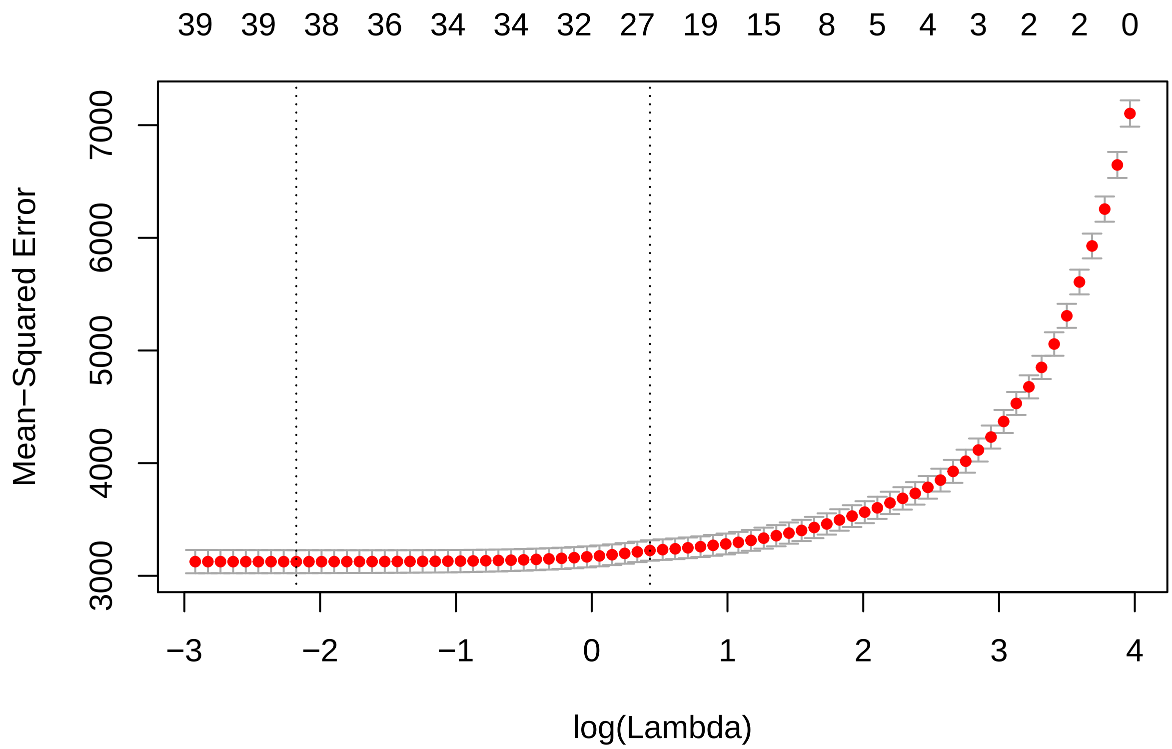

```r
cv.out.ddowntown <- cv.glmnet(x.boston.ddowntown,y.boston.ddowntown,alpha = 1)
plot(cv.out.ddowntown)
```




```
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)
```




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

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

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

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

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

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

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

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

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

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

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

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

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

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

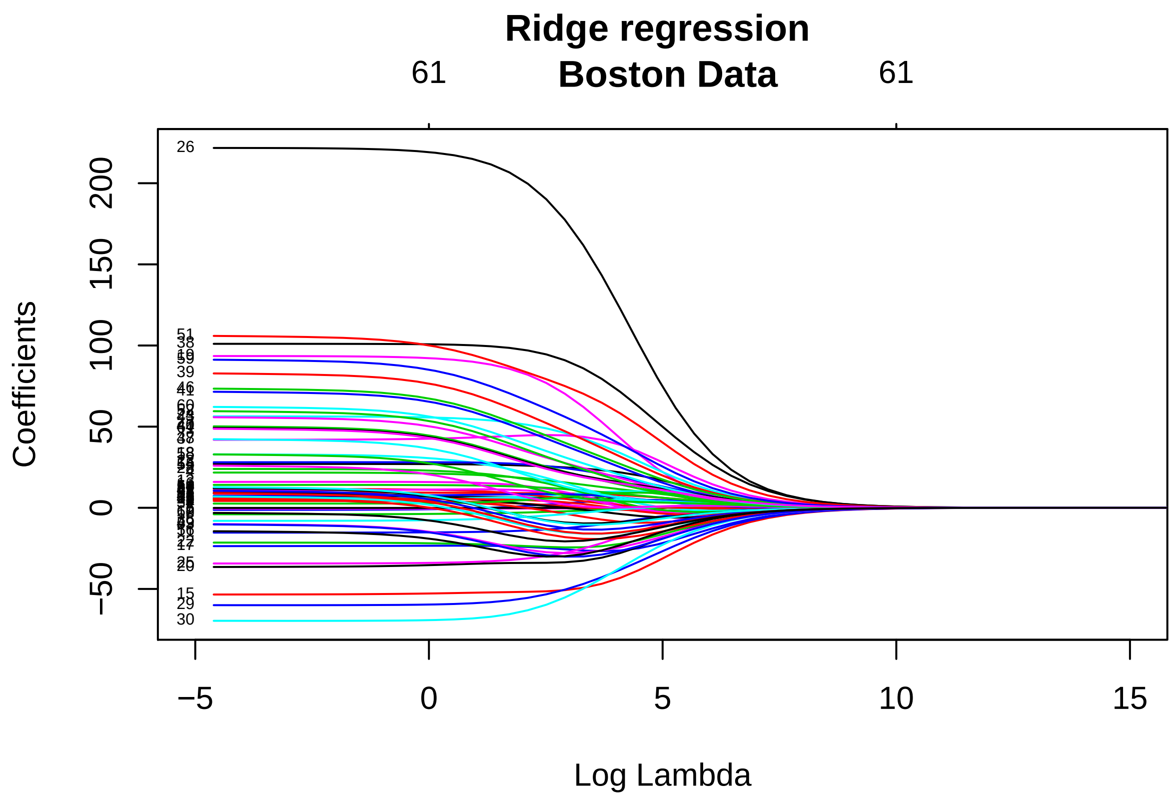
```r
cat("Best log lambda Boston Both" , log(bestlam.lasso.dboth), "\n")
```

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

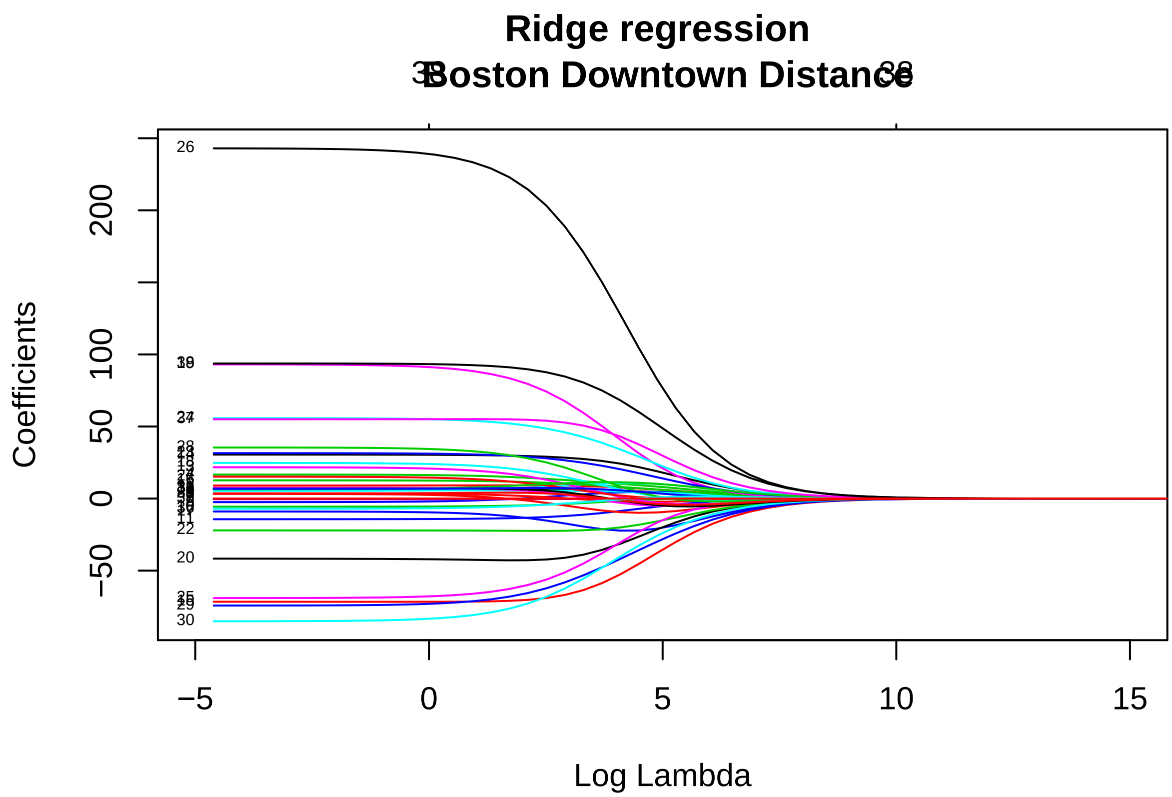
```r
lasso.model.data <- glmnet(x.boston.data, y.boston.data, alpha=1, lambda = bestlam.lasso.data)
lasso.model.ddowntown <- glmnet(x.boston.ddowntown, y.boston.ddowntown, alpha=1, lambda = bestlam.lasso
lasso.model.dairport <- glmnet(x.boston.dairport, y.boston.dairport, alpha=1, lambda = bestlam.lasso.dai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

Ridge Regression

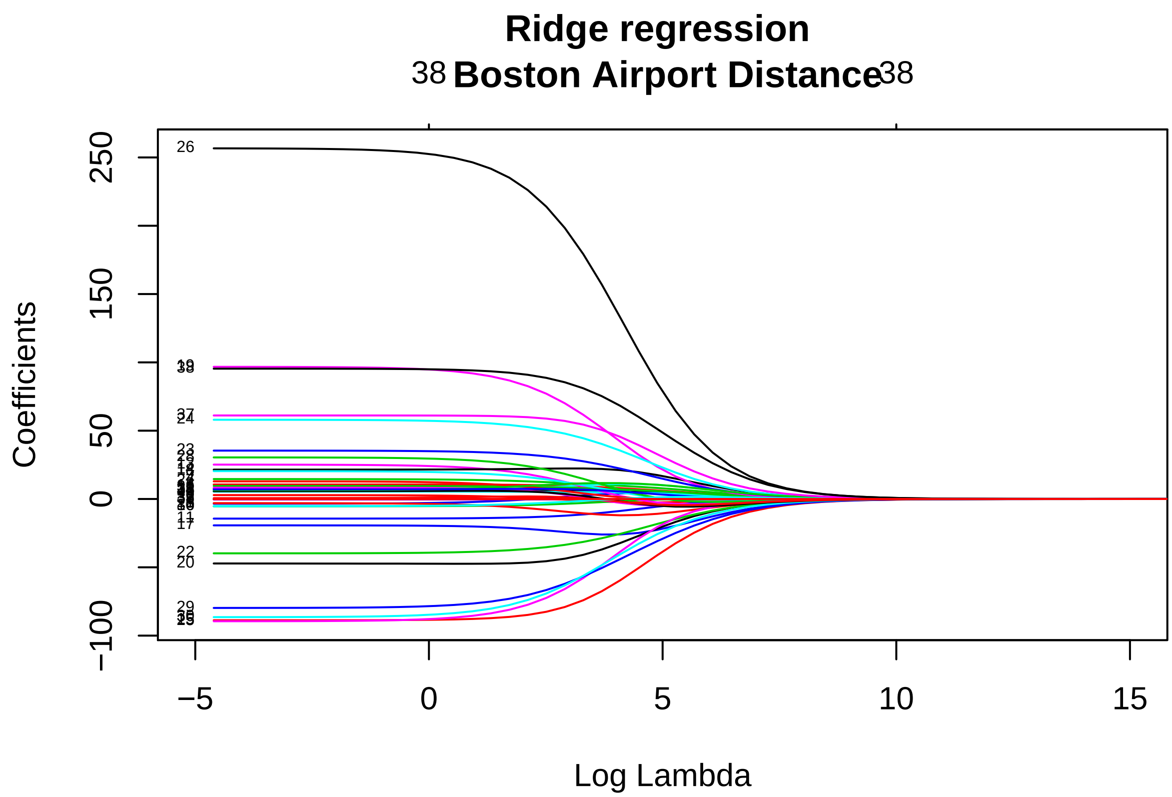
```r
grid = 10^seq(15,-2, length = 100)
ridge.boston.data <- glmnet(x.boston.data,y.boston.data, alpha = 0, lambda = grid)
plot(ridge.boston.data, main = "Ridge regression \n Boston Data", label = TRUE, xvar = "lambda", xlim =
```



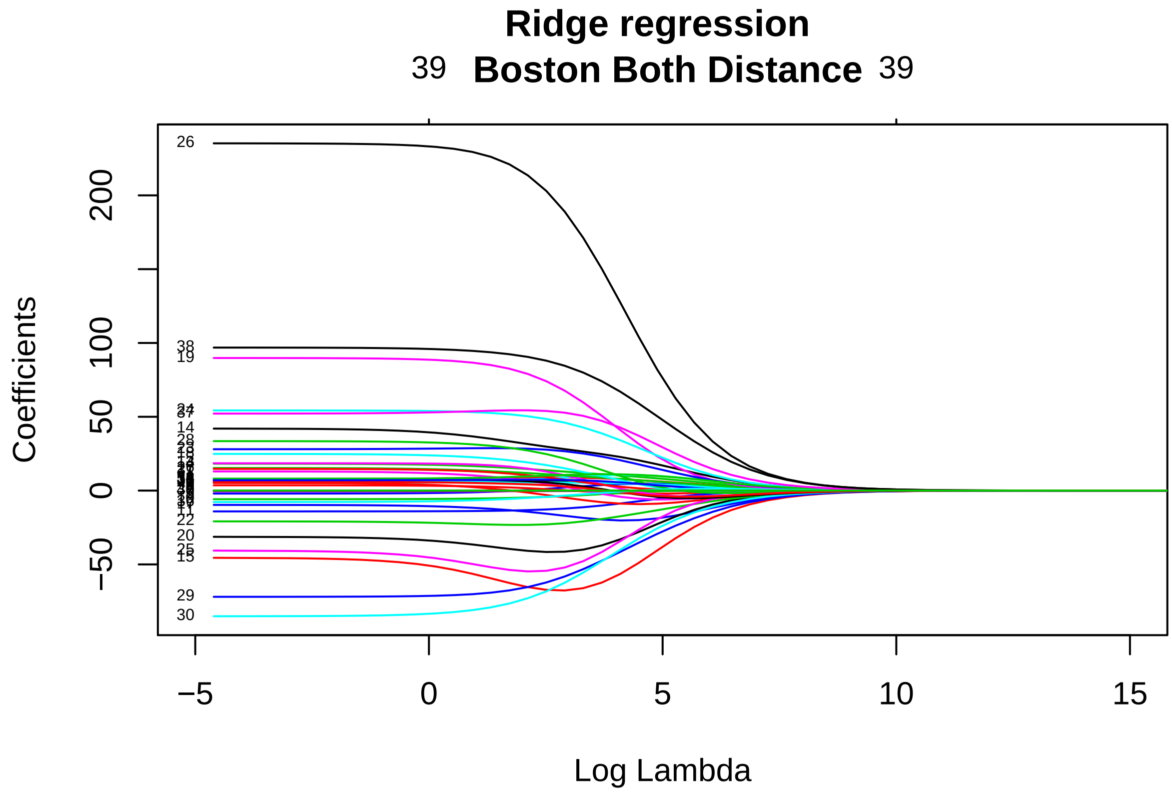

```r
ridge.boston.ddowntown <- glmnet(x.boston.ddowntown,y.boston.ddowntown, alpha = 0, lambda = grid)
plot(ridge.boston.ddowntown, main = "Ridge regression \n Boston Downtown Distance", label = TRUE, xvar =
```



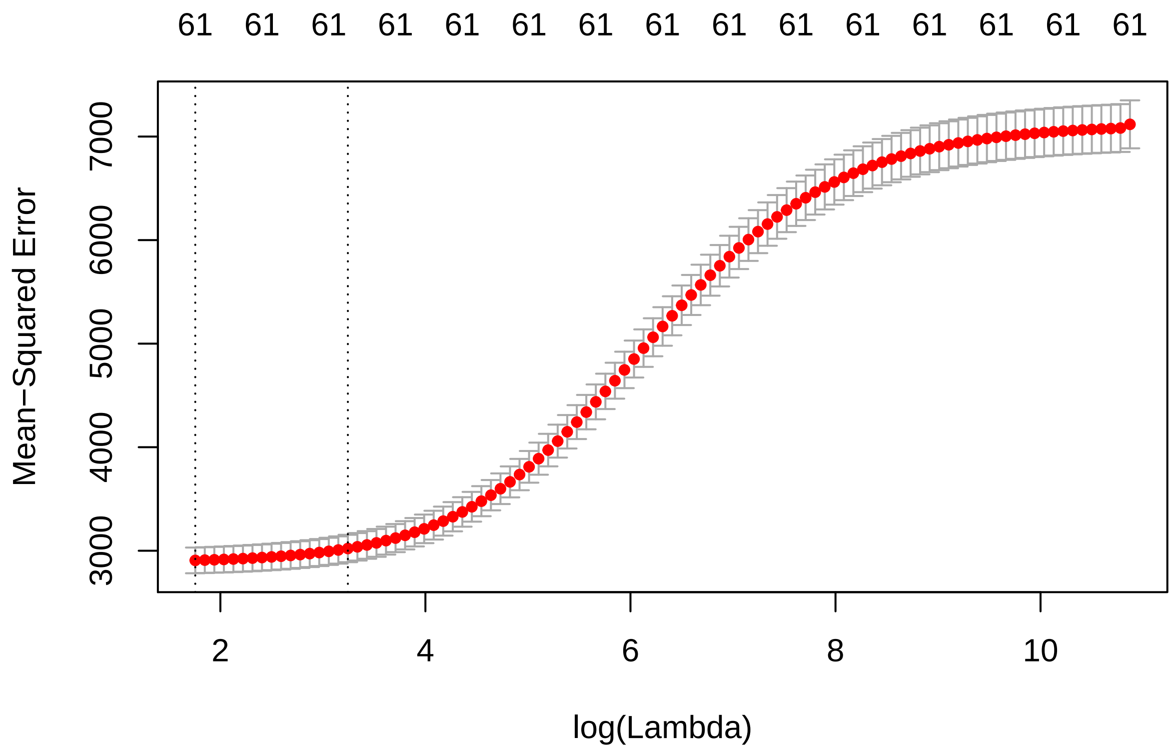

```
ridge.boston.dairport <- glmnet(x.boston.dairport,y.boston.dairport, alpha = 0, lambda = grid)
plot(ridge.boston.dairport, main = "Ridge regression \n Boston Airport Distance", label = TRUE, xvar =
```



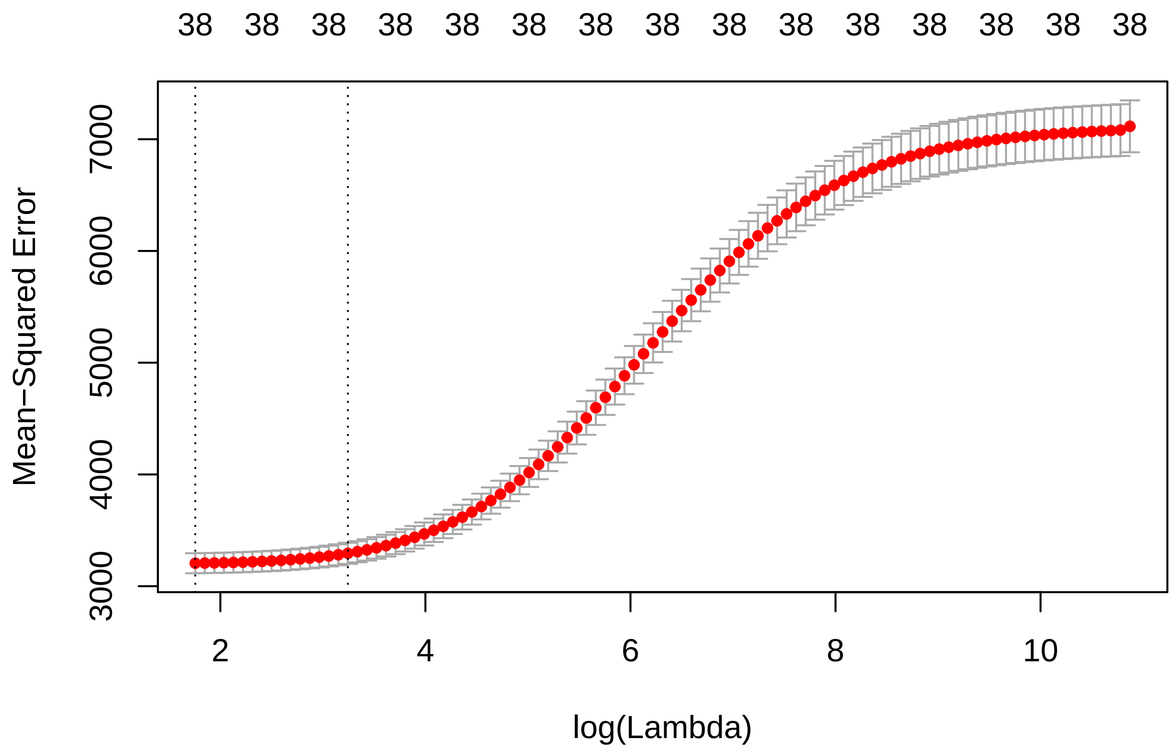

```r
ridge.boston.dboth <- glmnet(x.boston.dboth,y.boston.dboth, alpha = 0, lambda = grid)
plot(ridge.boston.dboth, main = "Ridge regression \n Boston Both Distance", label = TRUE, xvar = "lambda
```



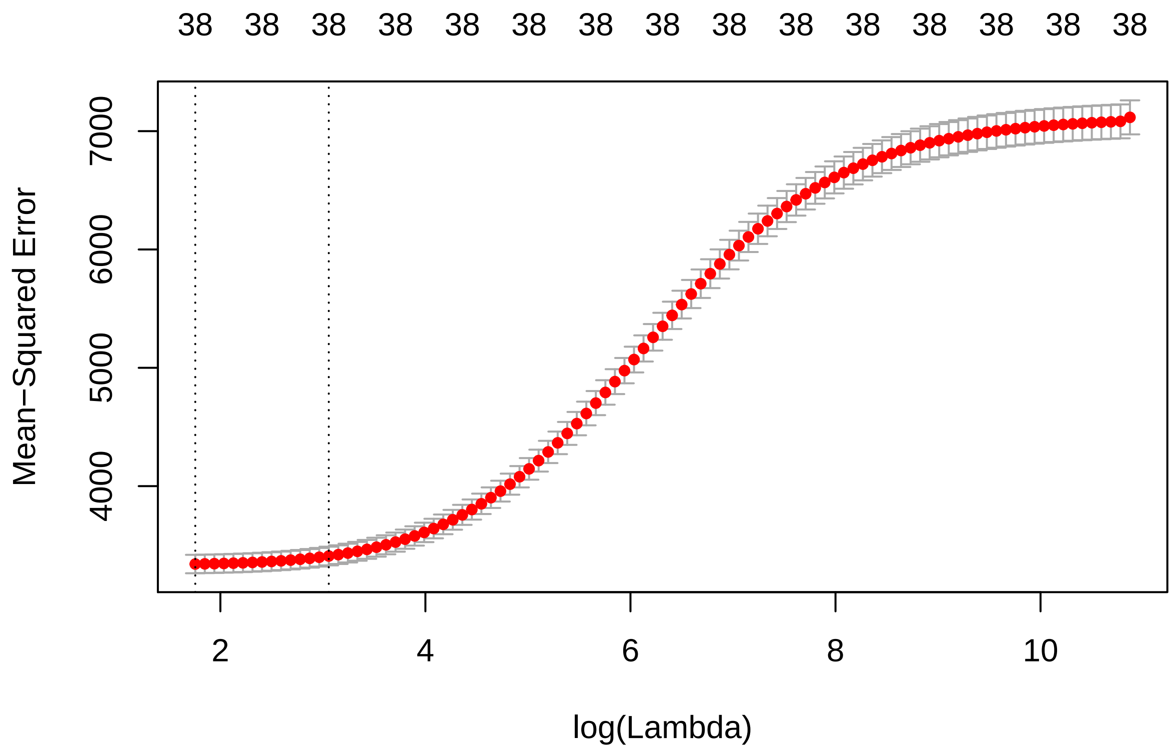

```r
cv.out.data <- cv.glmnet(x.boston.data,y.boston.data,alpha = 0)
plot(cv.out.data)
```



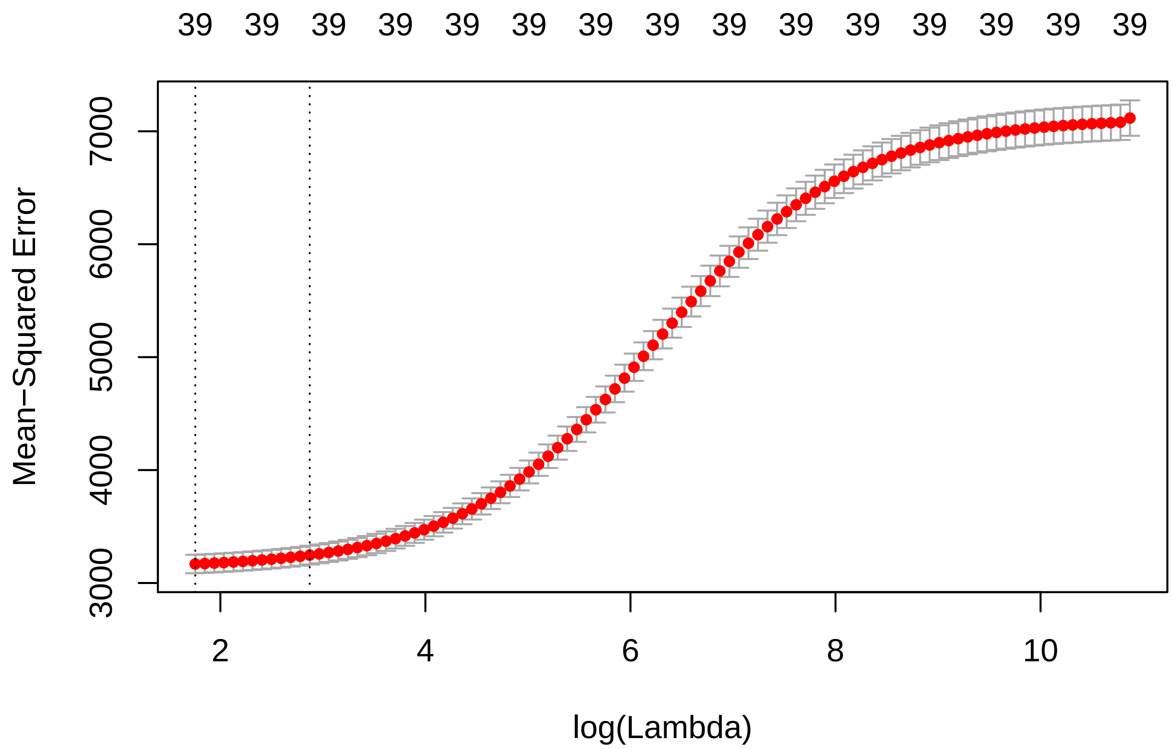

```
cv.out.ddowntown <- cv.glmnet(x.boston.ddowntown,y.boston.ddowntown,alpha = 0)
plot(cv.out.ddowntown)
```




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




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




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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

```
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)
```

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

print("LASSO")
```

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

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

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

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

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

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

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

```
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 $
```

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

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

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

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

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

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

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

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

```
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 $
```

```
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 $
```

```
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 $
```

```
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
```

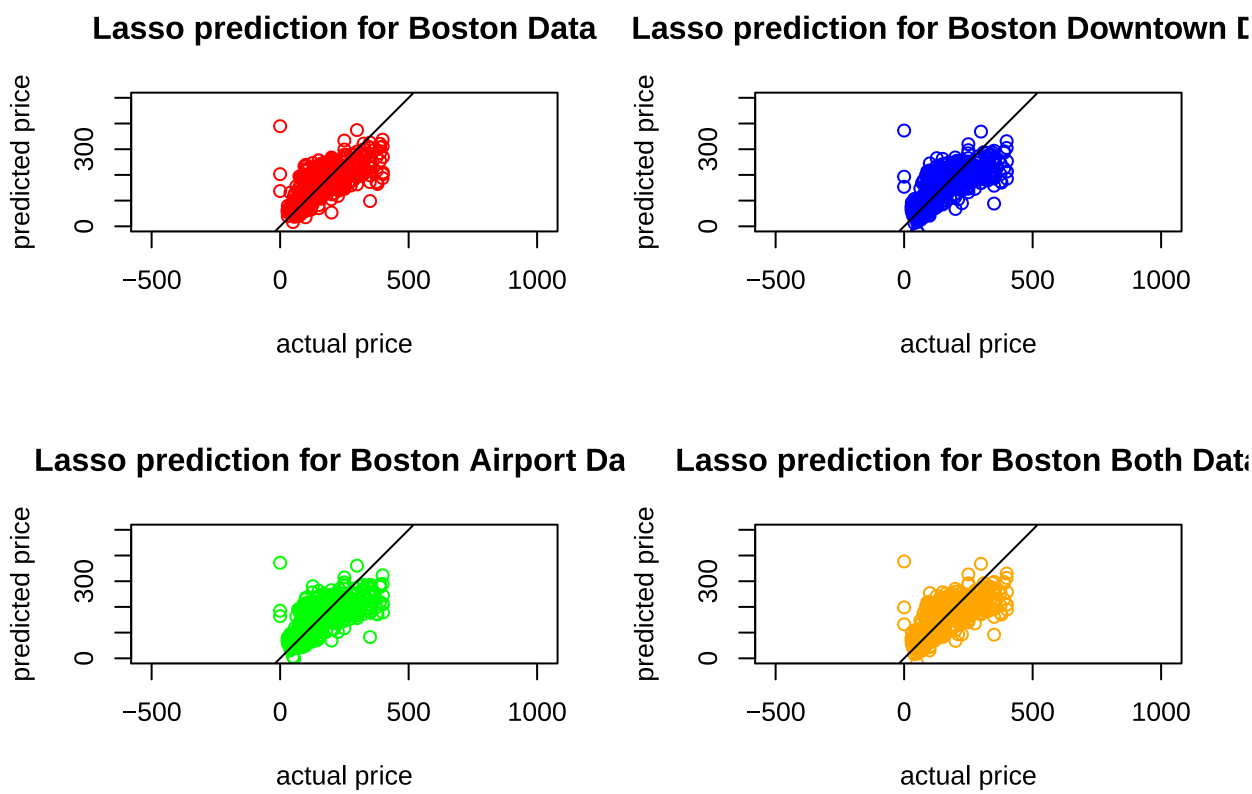
```r
a = predict(lasso.model.dairport, s = bestlam.lasso.dairport, type = "coefficients")
cat("Predictors for Lasso Boston Airport", nrow(a), "\n")
```

```
## 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

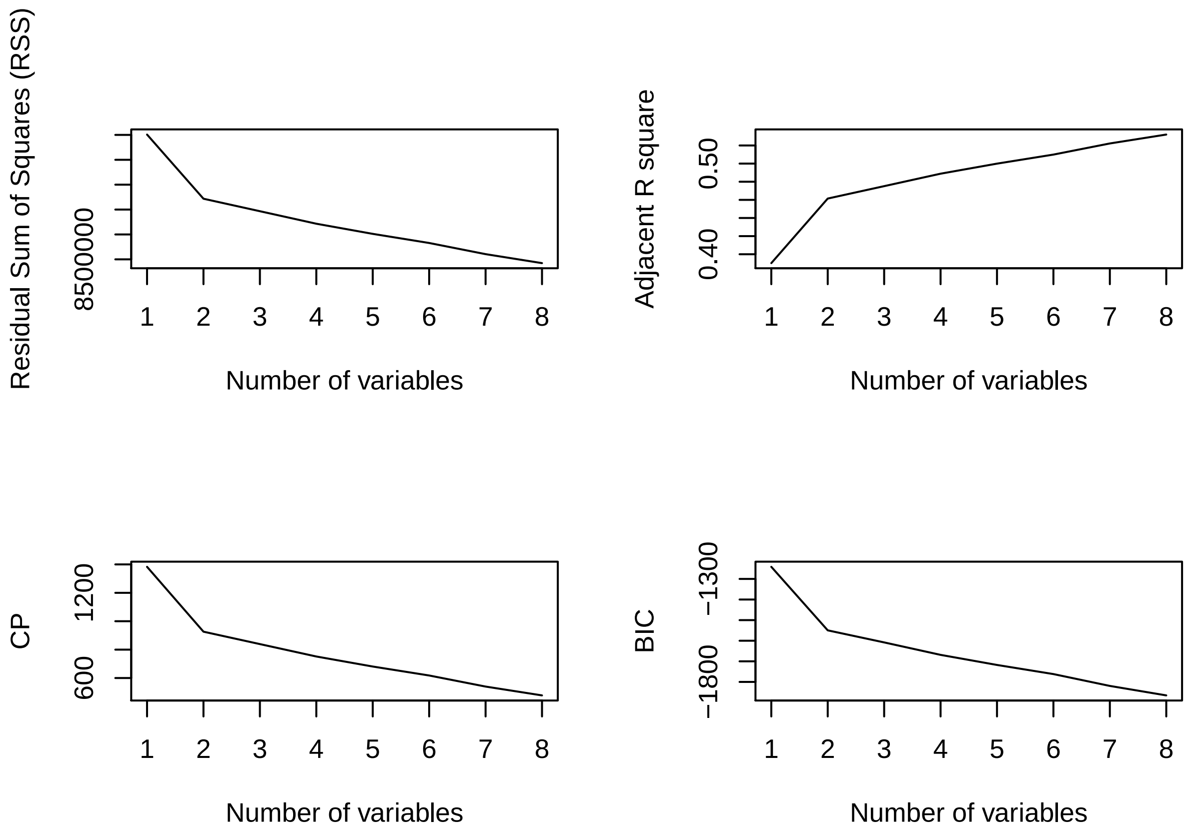
```r
# Helper function

## @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

```
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")
```




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

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

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

```
# 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
# 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

```
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

```r
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
```

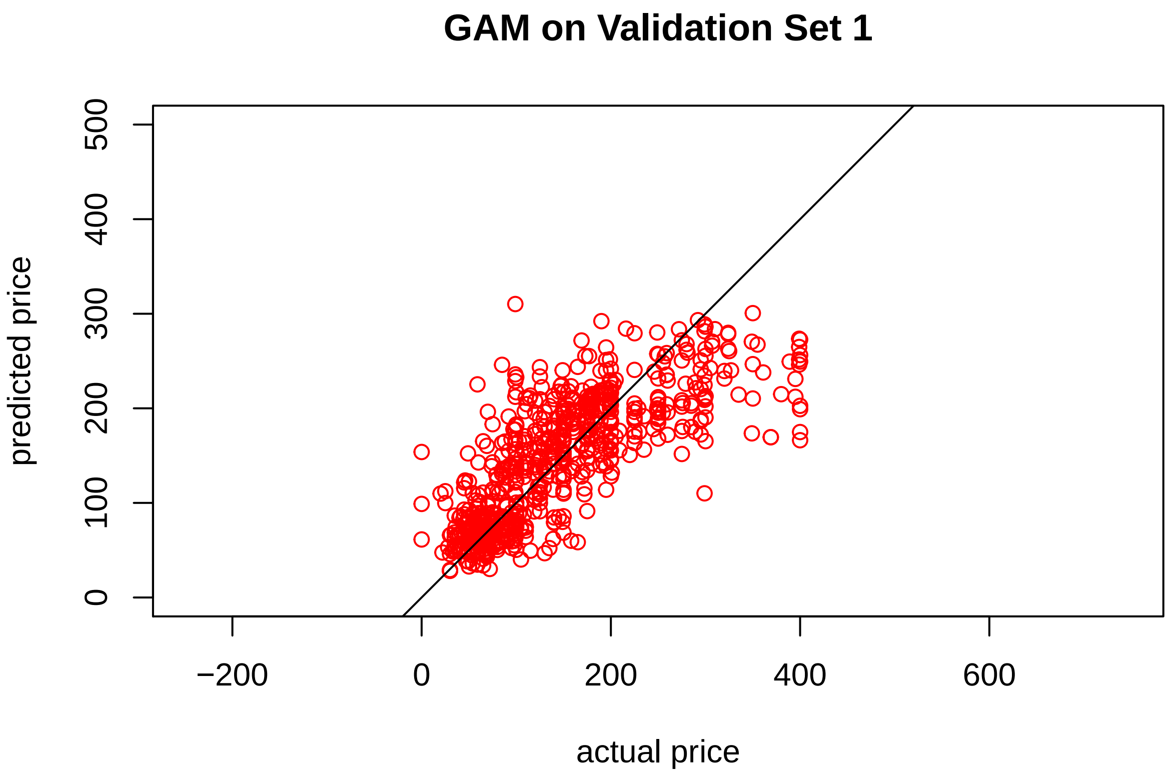
Results of the best model on validation_1 datasets

```
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

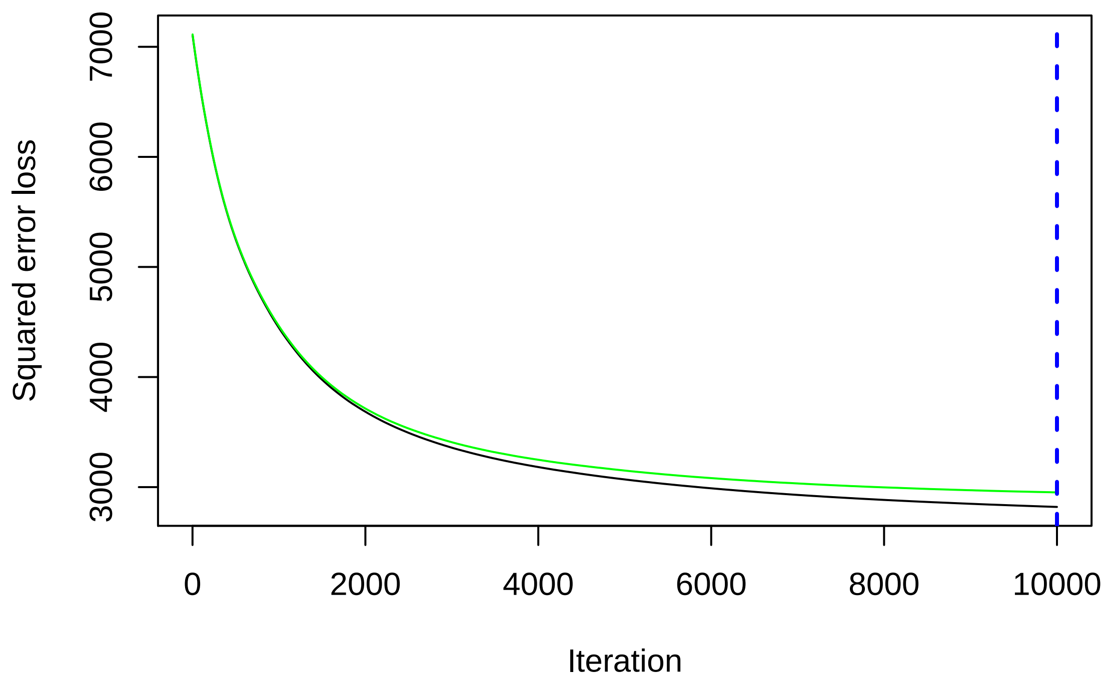
Train each of the transformations

```
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=10000
```

Results of neighborhoods

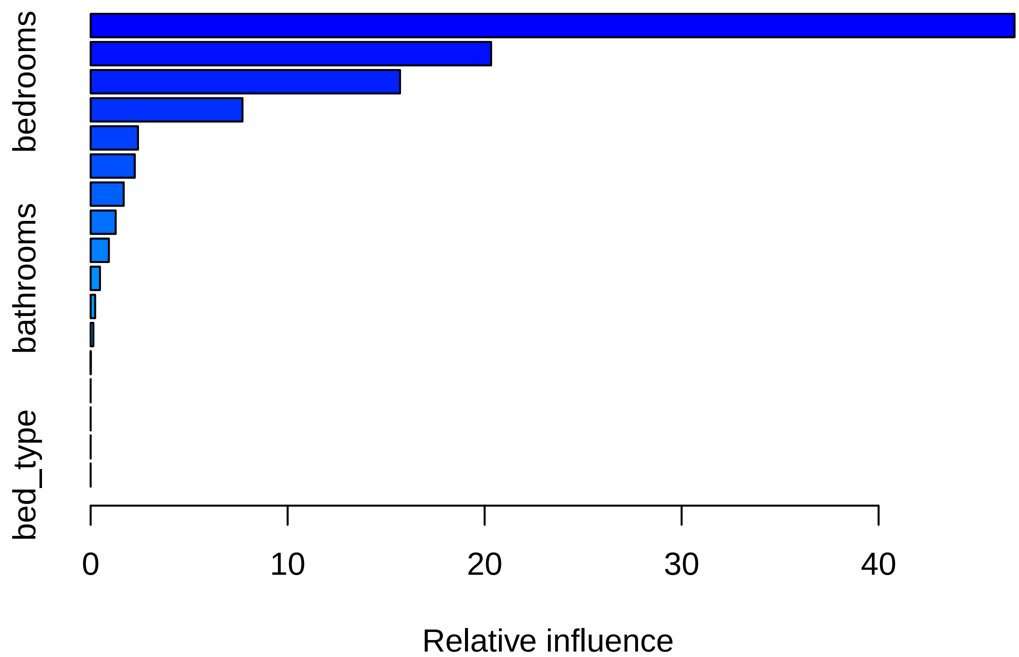
```r
gbm.perf(boston.data.boost)
```

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



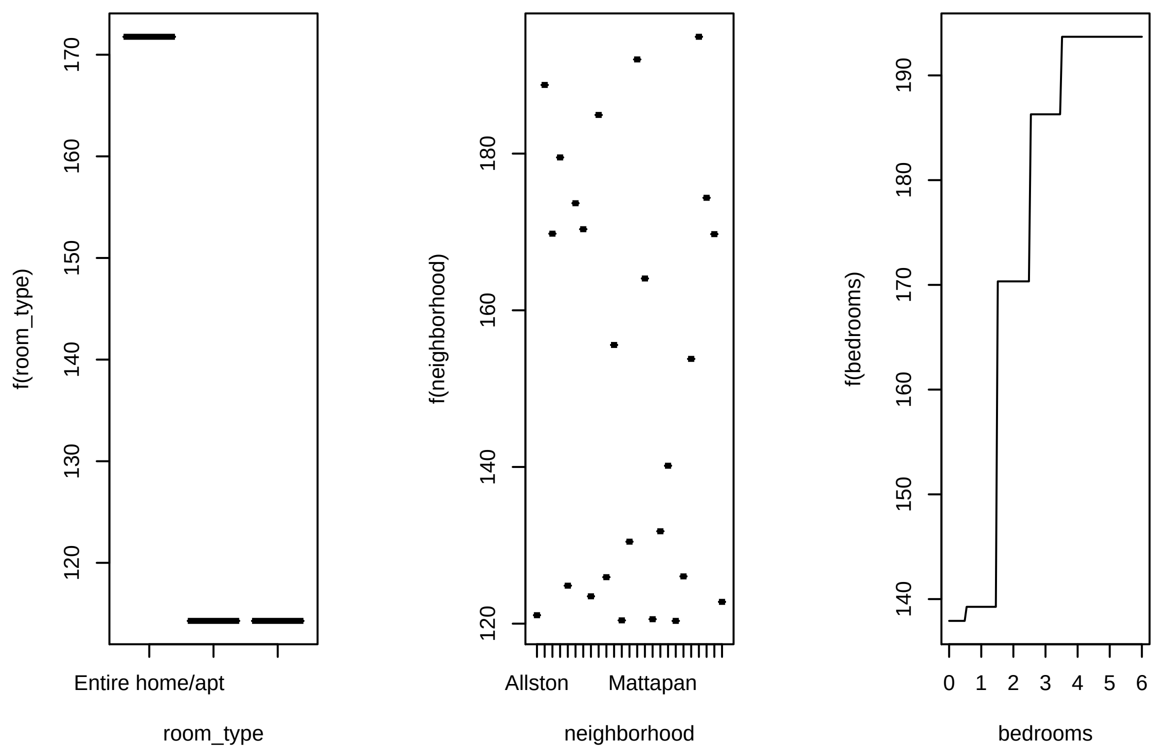

```
## [1] 10000
```

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

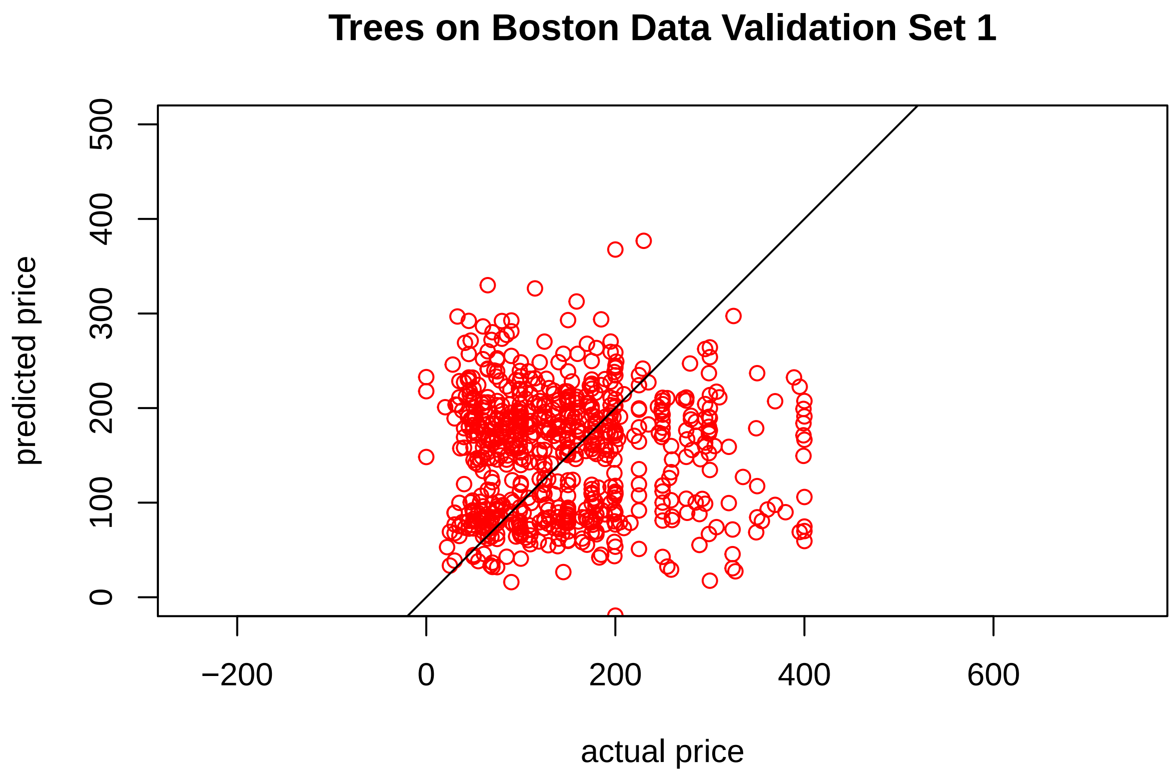



```
##                                                 var      rel.inf
## room_type                                 room_type 46.902021406
## neighborhood                           neighborhood 20.329109091
## bedrooms                                   bedrooms 15.704864188
## accommodates                           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
```

```
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=""))
```



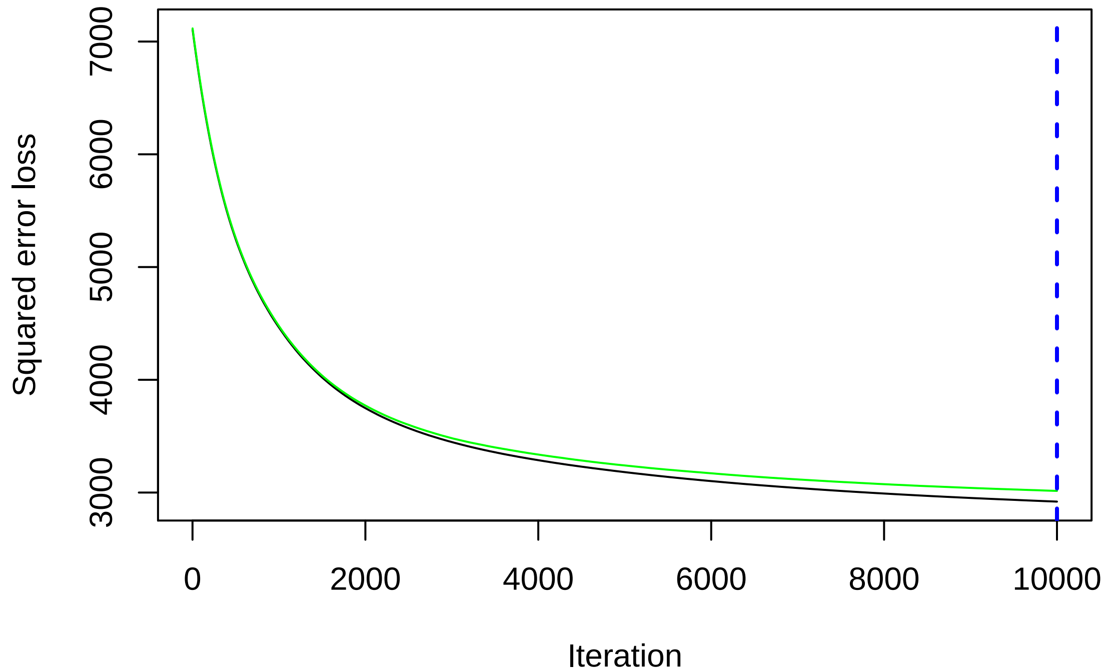

```
yhat <- predict(boston.data.boost, newdata=boston.data.validation_1)
## Using 10000 trees...
sqrt(mean((yhat - boston.data.validation_1.test)^2))
## [1] 55.74535
plot_predicts(yhat, boston.data.validation_1$price, "Trees on Boston Data Validation Set 1", "red")
```



Results of dboth

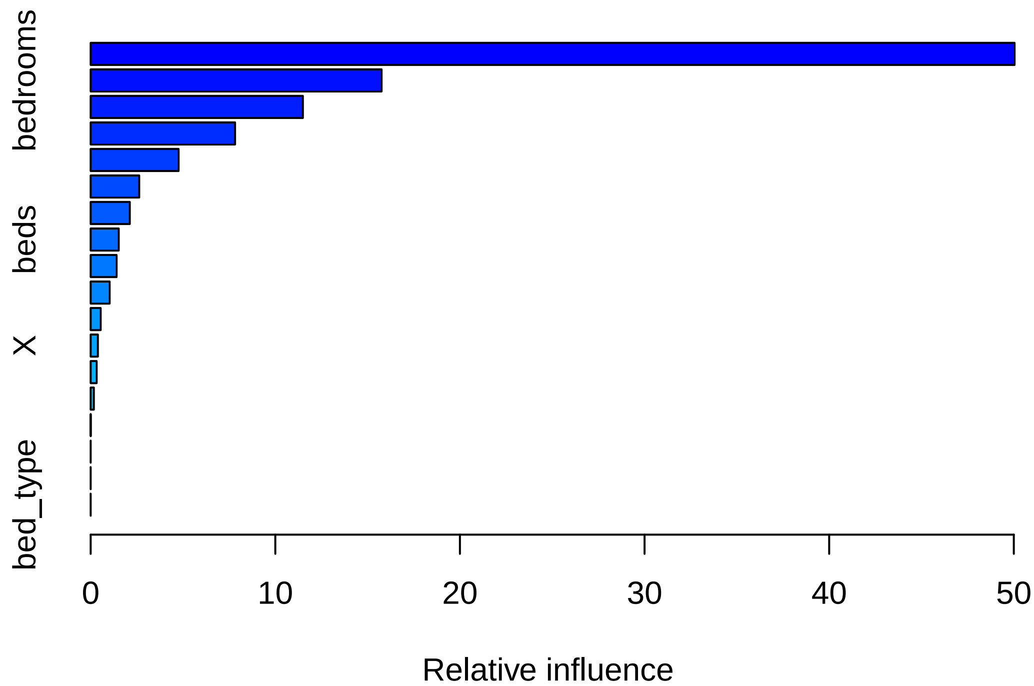
```
gbm.perf(boston.dboth.boost)
```

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



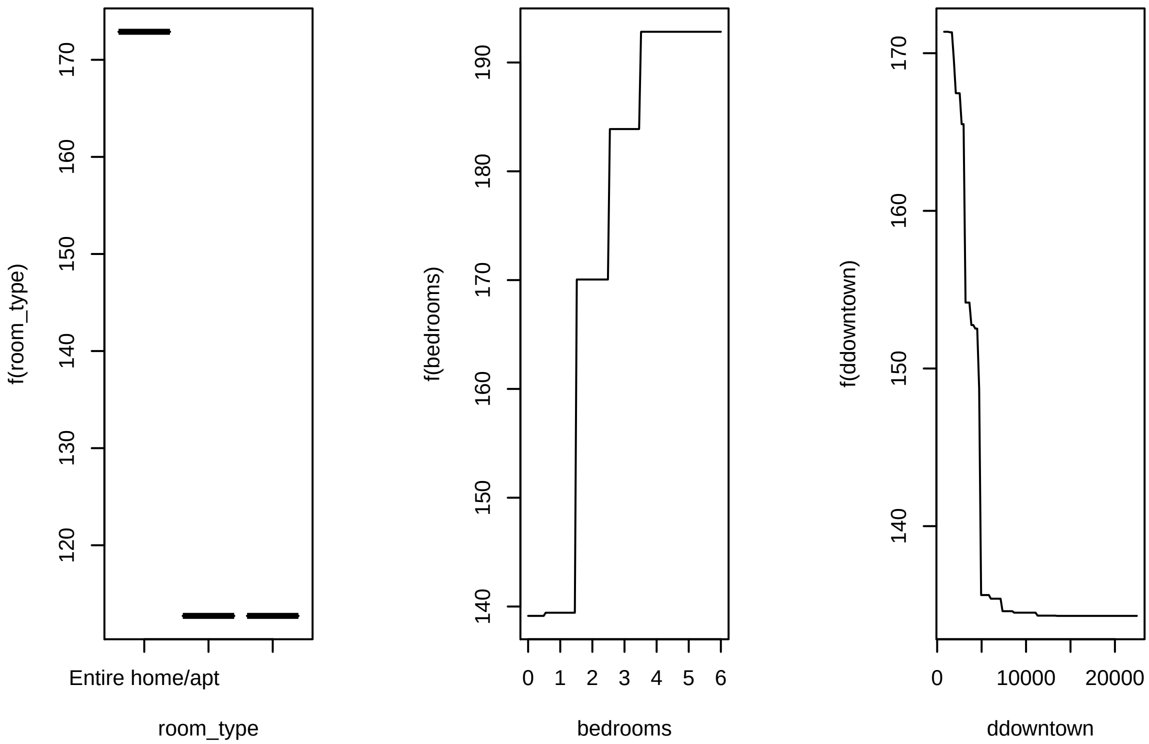

```
## [1] 10000
```

```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=""))
```



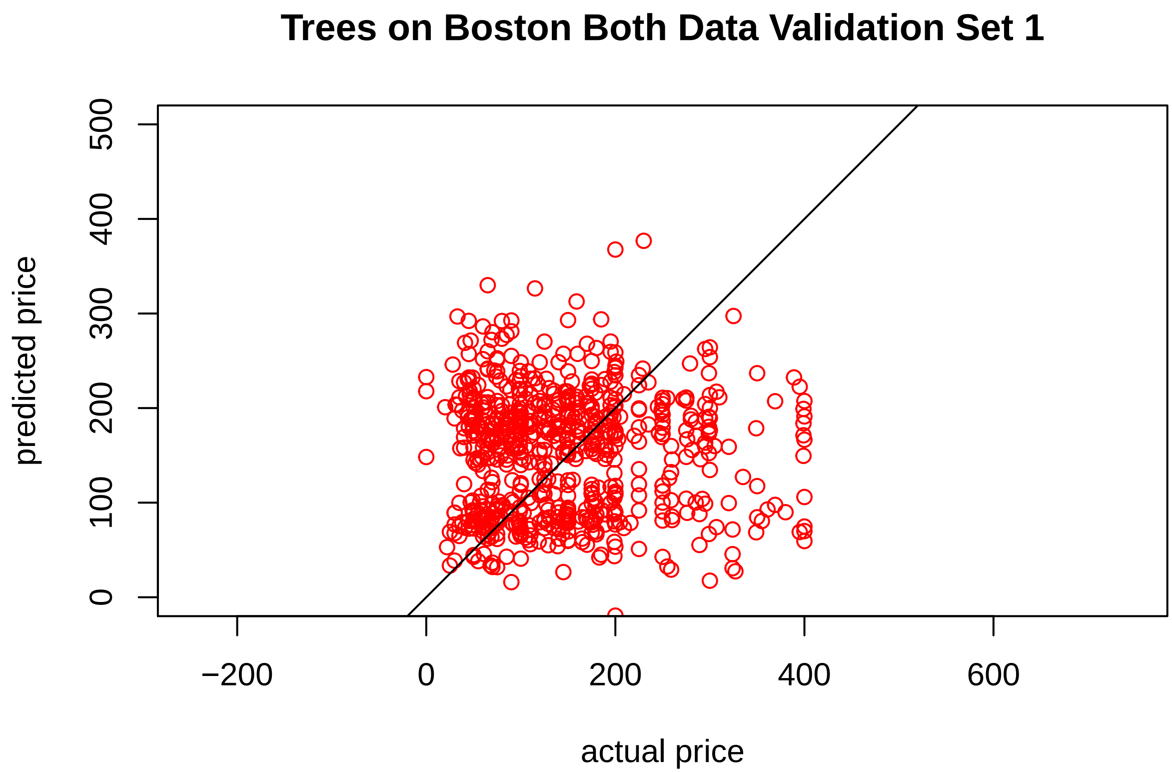

```
yhat <- predict(boston.dboth.boost, newdata=boston.dboth.validation_1)
```

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

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

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

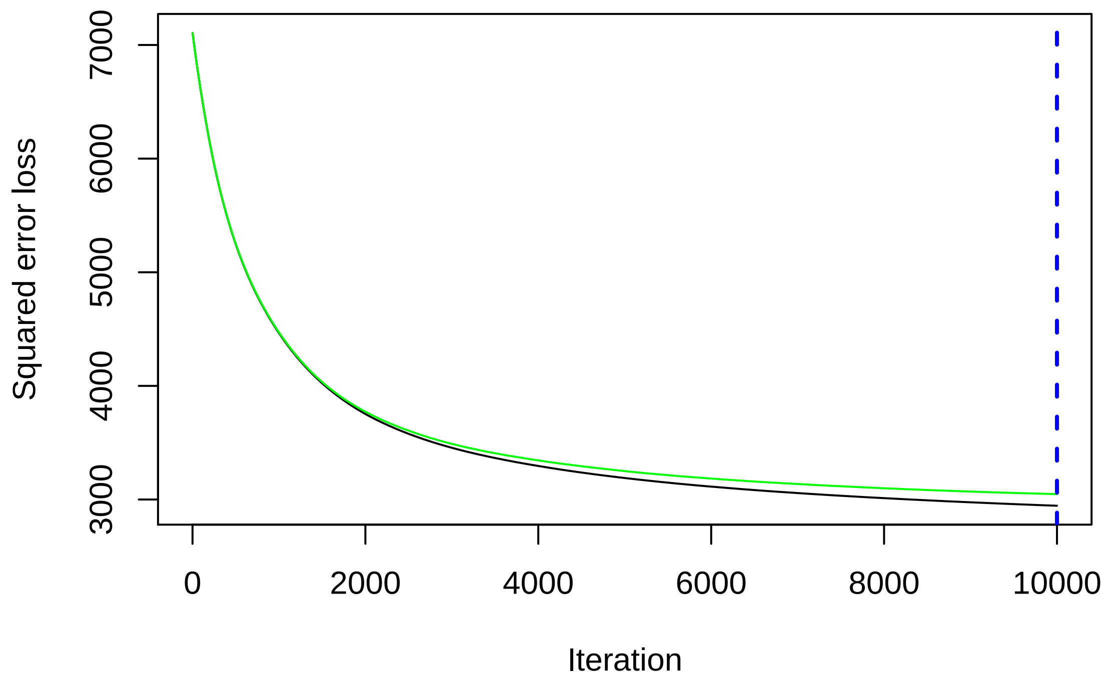
```
plot_predicts(yhat, boston.dboth.validation_1$price, "Trees on Boston Both Data Validation Set 1", "red
```



Results of ddowntown

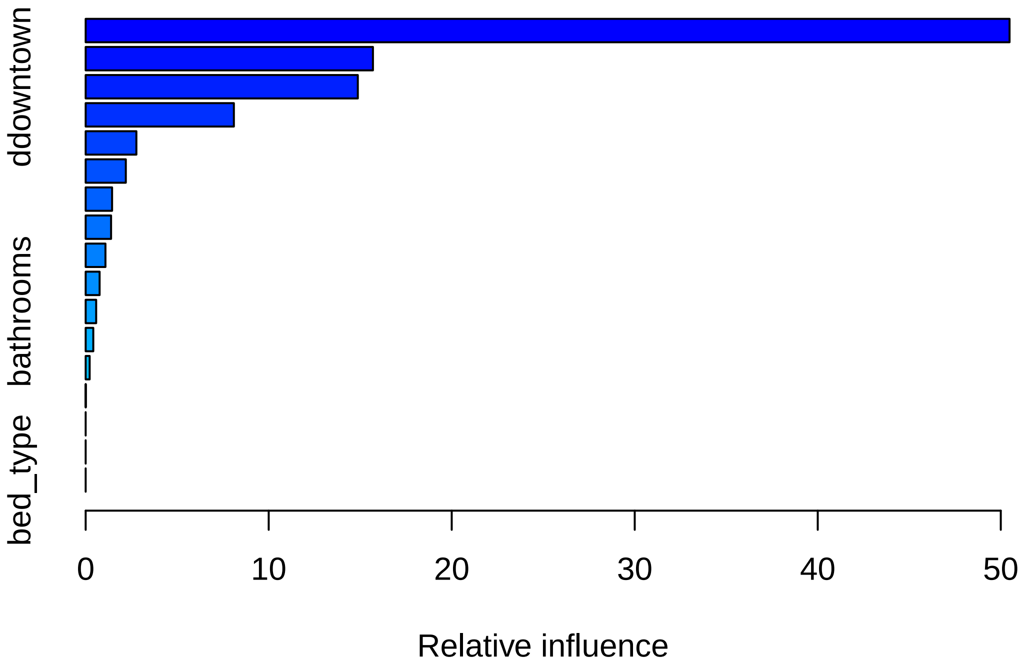
```r
gbm.perf(boston.ddowntown.boost)
```

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



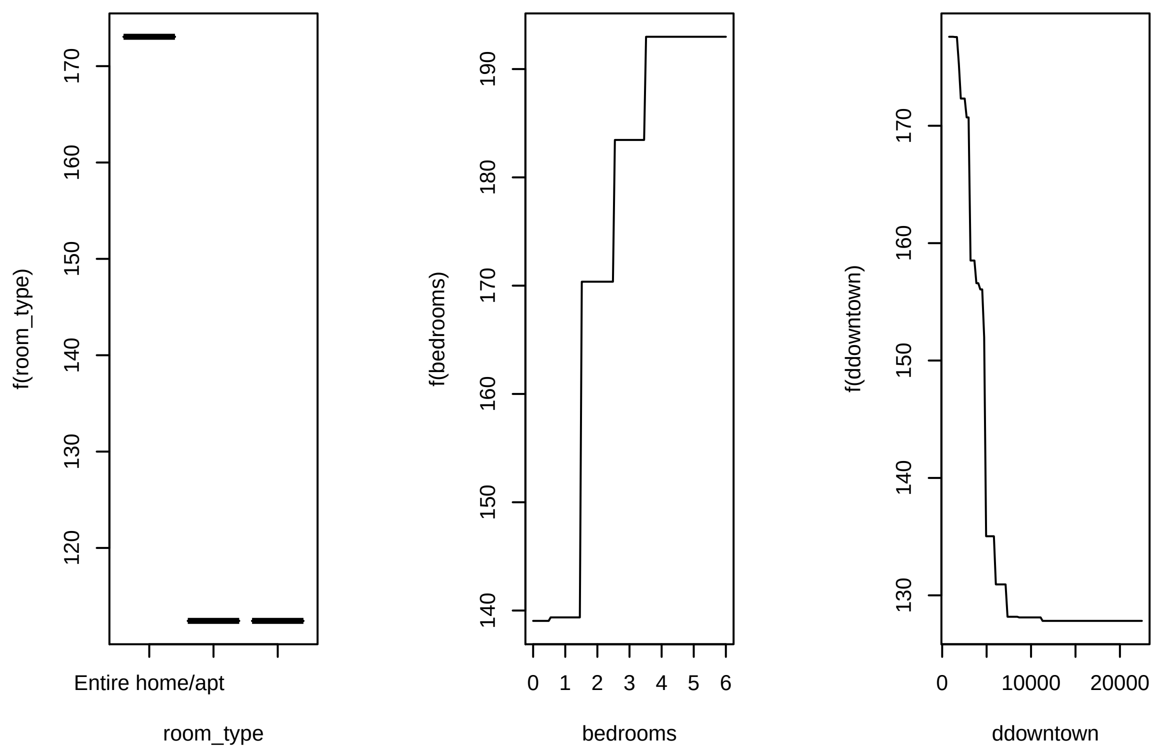

```
## [1] 10000
```

```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="")
```



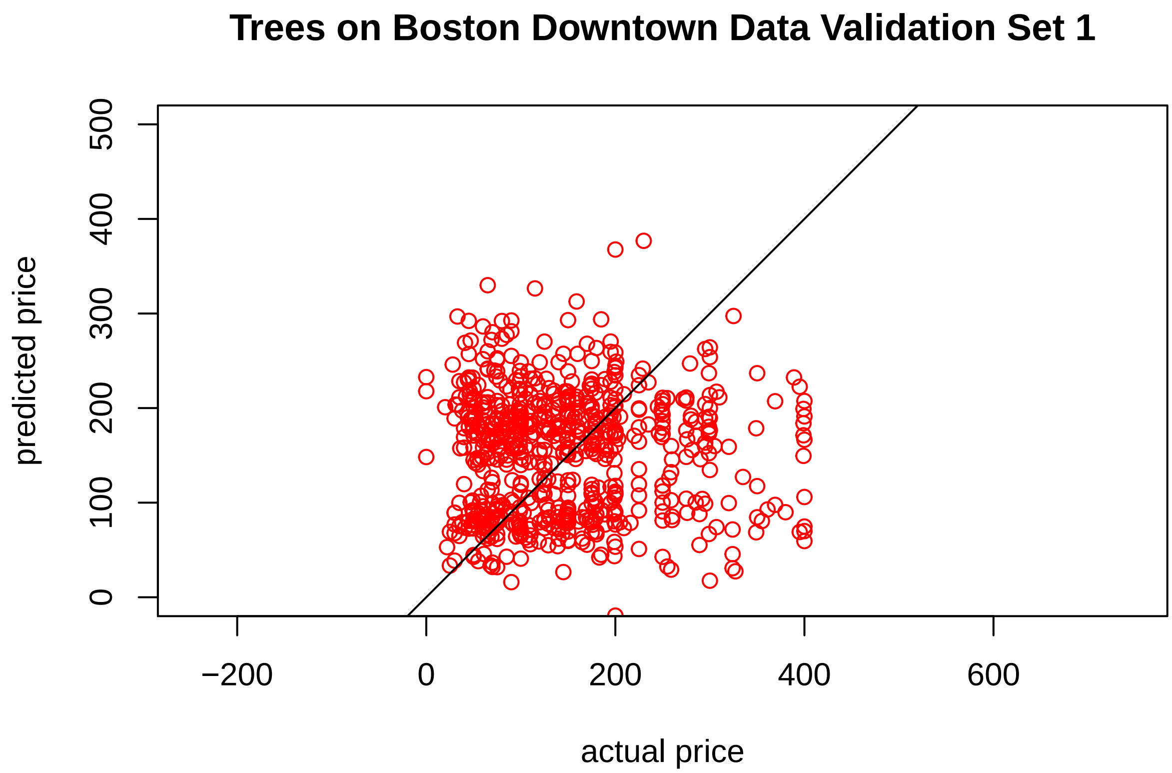

```
yhat <- predict(boston.ddowntown.boost, newdata=boston.ddowntown.validation_1)
```

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

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

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

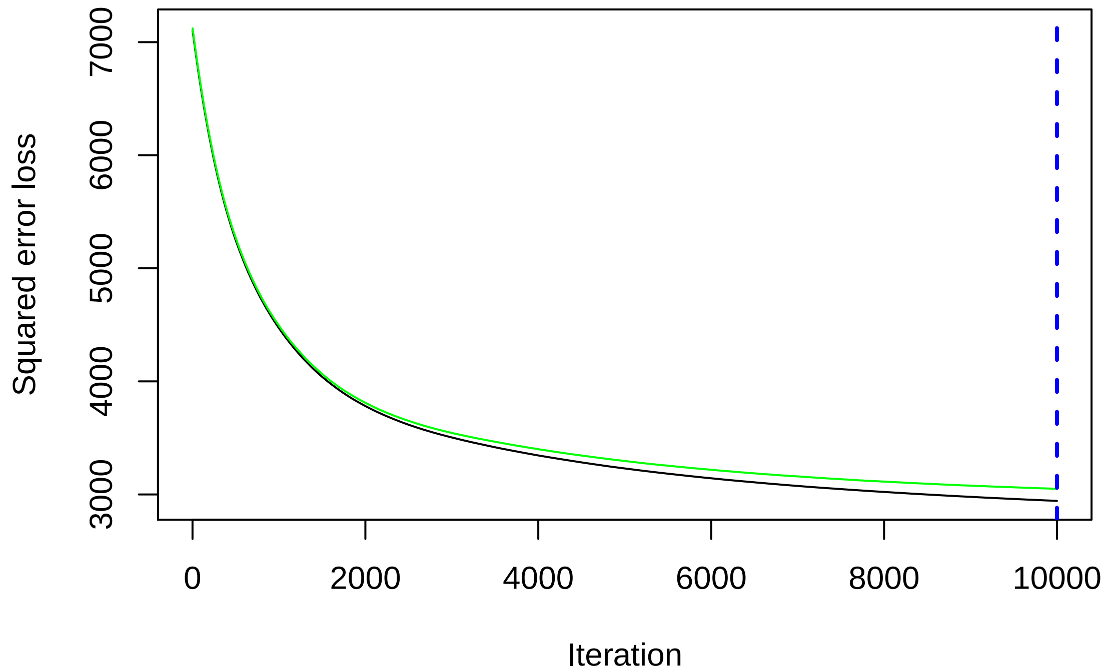
```
plot_predicts(yhat, boston.ddowntown.validation_1$price, "Trees on Boston Downtown Data Validation Set
```



Results of dairport

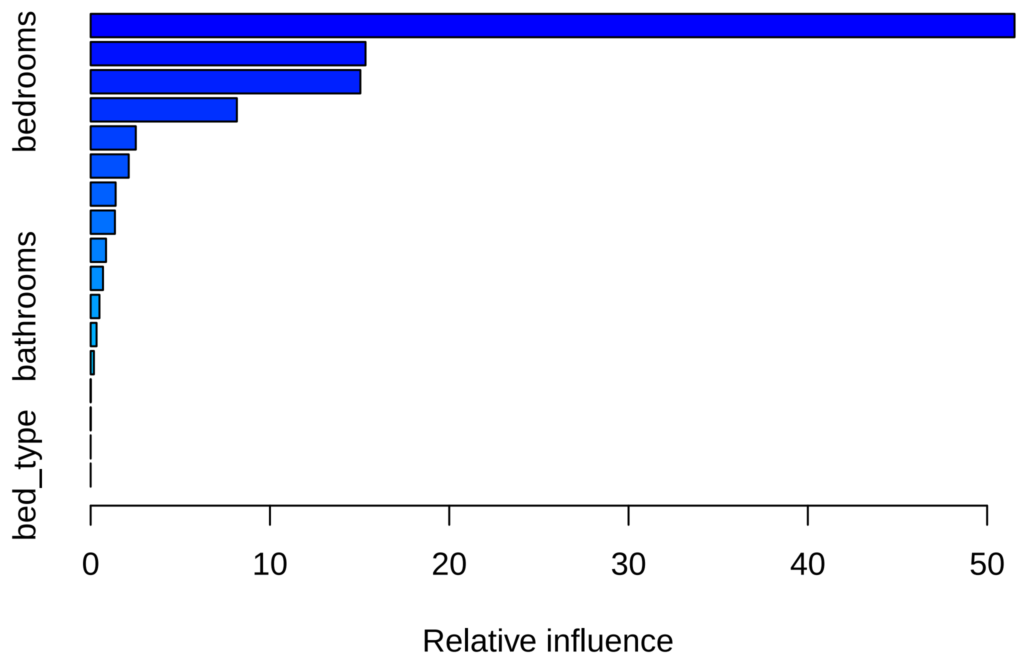
```
gbm.perf(boston.dairport.boost)
```

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



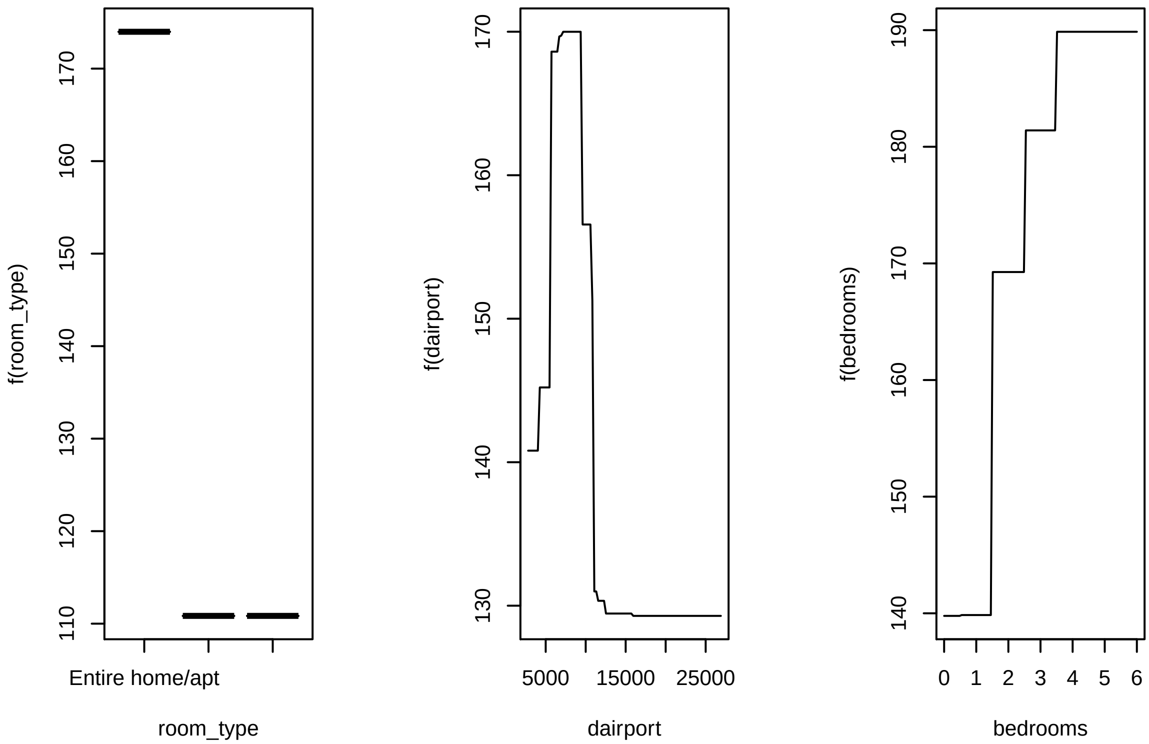

```
## [1] 10000
```

```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
```

```
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=""))
```



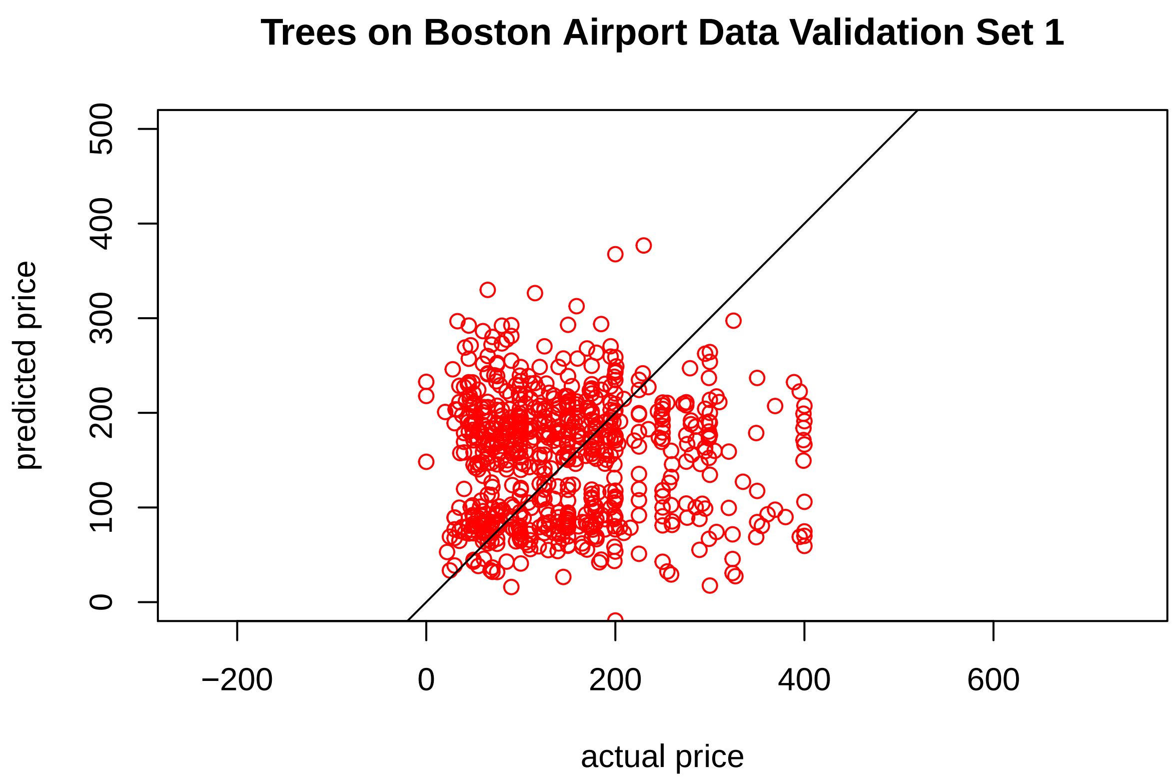

```r
yhat <- predict(boston.dairport.boost, newdata=boston.dairport.validation_1)
```

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

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

```
## [1] 56.5845
```

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



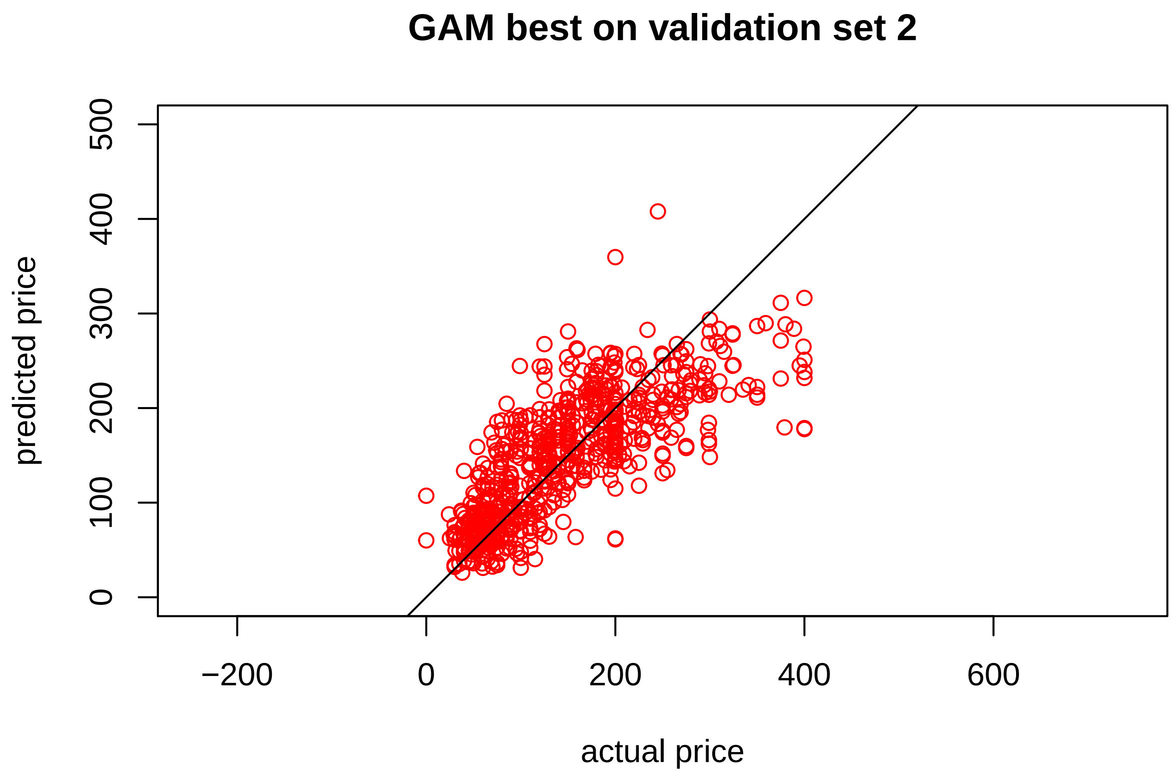
Best Model

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
0
100
200
300
400
500
−200
0
200
400
600
actual price

Statement of contributions

Abhay Kasturia

- Assisted in planning experimental design
- Assisted in transforming and separating datasets
- Performed analysis using Linear Regression methods
- Assisted in writing and editing presentation
- Assisted in writing and editing report

Nakul Camasamudram

- Assisted in planning experimental design
- Assisted in transforming and separating datasets
- Researched and performed analysis using Generalized Additive Models
- Assisted in writing and editing presentation
- Assisted in writing and editing report

Philip Parker

- Assisted in planning experimental design
- Assisted in transforming and separating datasets
- Performed analysis using tree methods
- Assisted in writing and editing presentation
- Assisted in writing and editing report