Boston Housing Evaluation

Project Report submitted by

Rekha Rao

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TABLE OF CONTENTS

Contents

Preface

I started pursuing Data Science during the lockdown of COVID19. What started out as a hobby, soon became a passion as I found R programming pretty interesting.

I could do this through the online courses offered by Harvard University (edX) which really suited my purpose as I work as a full time IT Project Manager as well.

I completed the 8 courses for Data Science and now submitting this project for course 9 – Capstone.

I found Capstone challenging but at the same time fun because it helped me apply a lot of the machine learning concepts that I had learnt in the previous Machine Learning course.

I hope to apply my learning to many more Data Science projects in the future.

1. Introduction

The Boston Housing dataset is one of the most popular datasets to be used for Regression and Machine learning. The data comprised in this dataset was collected by the U.S Census Service and it first appeared in the history of statistical analysis in a paper by David Harrison Jr. and Daniel L Rubinfield called Hedonic Housing prices and the demand for Clean Air.

a. Structure of the Report

Section 1 presents the introduction, Objective and Overview for the Project.

Section 2 presents the Data Preparation – Data processing and Data cleanup if any as required.

Section 3 presents the Exploratory Data Analysis – Looking at correlation between variables using Data Visualization.

Section 4 presents the fitting of the different models.

Section 5 presents the Conclusion – selection of the final Model.

Section 6 presents the limitations of the model.

Section 7 contains the references.

b. Objective

The objective is to build a machine learning model to predict the Median value (MEDV) of owner occupied homes in Boston based on the available features.

This report provides an analysis and evaluation of certain factors affecting the median value of the owner occupied homes in the suburbs of Boston.

c. Overview

i. Data set Source

This data has been downloaded from Kaggle . Kaggle is an online platform for data scientists and machine learning students.

Since Kaggle does not allow us to download the files directly , I have downloaded the file to my github and here is the link to the file:

https://github.com/rrao2511/CYO-Harvard-Capstone-Project/raw/main/housing.csv

ii. Data set Description

The original Boston housing dataset contains 506 samples and 14 variables.

For the purpose of this report we will be looking only at a subset of the original Boston housing dataset.

Our dataset contains 489 samples and 4 variables which are explained below:

MEDV – Median Value of Owner occupied homes

RM - Average number of rooms per dwelling

LSTAT - % lower status of population

PT RATIO - Pupil teacher ratio by town

This dataset did not require much of data preprocessing as it is already normalized

More details of steps to be followed is outlined in the Approach section.

iii. Goal of Analysis

The goal of our analysis is to select the best prediction model which can predict the Median value of owner occupied homes in Boston.

d. Approach

In order to reach our goal of building the most effective prediction model , we will follow the steps outlined below:

i. Data Structure

Here we will look at the data structure, dimensions and summary.

ii. Data Preparation and Cleansing

Normally the dataset we use for prediction needs to be cleaned up. But this housing dataset has already been normalized and it does not need cleanup.

But we will be checking to see if there are any missing or duplicated values in the dataset.

iii. Exploring the data (Data Analysis) including Data Visualization

Here we will explore the data set to see the correlation between variable and use Data Visualization techniques.

iv. Development of Models

We will first split up the data into Training and Test data.

Here we will be working on three different models, namely:

❖ Decision Tree Model

A decision tree is a supervised learning algorithm used for both classification and regression tasks. It creates a tree-like model of decisions and their possible consequences, including chance events and resource costs. Each internal node of the tree represents a decision rule based on one or more features, and each leaf node represents a predicted outcome.

Decision trees can be applied to a variety of datasets, including numerical, categorical, and ordinal data.

In the case of the Boston Housing dataset, decision trees can be used to predict the median value of owner-occupied homes in different neighborhoods based on a set of features such as the average number of rooms per dwelling and other factors.

Overall, decision trees are useful for the Boston Housing model because they provide a simple yet powerful method for predicting house prices based on a set of input features.

- Random Forest Model

  Random Forest is a popular ensemble learning method used in machine learning for classification and regression tasks.

  Random Forest can be applied to a wide range of datasets, including those with high dimensionality, non-linear relationships, and mixed data types.

  One of the main advantages of Random Forest is that it can provide accurate predictions even in the presence of correlated or redundant features, which can cause problems for other machine learning models.

  Random Forest is useful for the Boston Housing model because it provides an accurate and robust method for predicting house prices based on a set of input features.

  It can also help to reduce overfitting.

- Support Vector Machine (SVM) Model.

  One of the main advantages of SVM is that it can handle both linear and non-linear relationships between features and the target variable, thanks to the use of kernel functions.

  SVM is useful for the Boston Housing model because it provides a powerful and flexible method for predicting house prices based on a set of input features.

v. Results

The measure of performance that is being used is RMSE – Root Mean Square Error. It measures the average difference between values predicted by the model and the actual values.

RMSE is well-suited for evaluating models built using the Boston Housing dataset because it is sensitive to the magnitude of errors in the predictions. In other words, RMSE penalizes large errors more heavily than small errors, which is important when predicting house prices that can vary significantly in value.

The lower the RMSE, the better a given model is able to “fit” a dataset.

The RMSE for the three methods will be tabulated for comparison.

vi. Recommendation of the Model

We are using RMSE – Root Mean square to assess the performance of these models.

The model with the lowest RMSE is the best fit for the data.

vii. Limitations for this Model.

The limitations for these models will be outlined with suggestions for possible improvement.

2. Data Preparation and Data Preprocessing

Dataset Source:

Kaggle is an online platform for data scientists and machine learning students.

This particular dataset - Boston housing has been downloaded from Kaggle.

First step - download the Packages needed for this analysis and load the libraries.

```
if(!require(tidyverse)) install.packages("tidyverse", repos = "http://cran.us.r-project.org")
```

```
## Loading required package: tidyverse
```

```
## Warning: package 'tidyverse' was built under R version 4.1.3
```

```
## Warning: package 'ggplot2' was built under R version 4.1.3
```

```
## Warning: package 'tibble' was built under R version 4.1.3
```

```
## Warning: package 'tidyr' was built under R version 4.1.3
```

```
## Warning: package 'readr' was built under R version 4.1.3
```

```
## Warning: package 'purrr' was built under R version 4.1.3
```

```
## Warning: package 'dplyr' was built under R version 4.1.3
```

```
## Warning: package 'stringr' was built under R version 4.1.3
```

```
## Warning: package 'forcats' was built under R version 4.1.3
```

```
## Warning: package 'lubridate' was built under R version 4.1.3
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.1     v readr     2.1.4
## v forcats   1.0.0     v stringr   1.5.0
## v ggplot2   3.4.2     v tibble    3.2.1
## v lubridate 1.9.2     v tidyr     1.3.0
## v purrr     1.0.1
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
e errors
```

```
if(!require(ggplot2)) install.packages("ggplot2", repos = "http://cran.us.r-project.org")
if(!require(dplyr)) install.packages("dplyr", repos = "http://cran.us.r-project.org")
if(!require(corrplot)) install.packages("corrplot", repos = "http://cran.us.r-project.org")
```

```
## Loading required package: corrplot
```

```
## Warning: package 'corrplot' was built under R version 4.1.3
```

```
## corrplot 0.92 loaded
```

```
if(!require(randomForest)) install.packages("randomForest", repos = "http://cran.us.r-project.or
g")
```

```
## Loading required package: randomForest
```

```
## Warning: package 'randomForest' was built under R version 4.1.3
```

```
## randomForest 4.7-1.1
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
##
## The following object is masked from 'package:dplyr':
##
##     combine
##
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```
if(!require(rpart)) install.packages("rpart", repos = "http://cran.us.r-project.org")
```

```
## Loading required package: rpart
```

```
if(!require(caret)) install.packages("caret", repos = "http://cran.us.r-project.org")
```

```
## Loading required package: caret
```

```
## Warning: package 'caret' was built under R version 4.1.3
```

```
## Loading required package: lattice
##
## Attaching package: 'caret'
##
## The following object is masked from 'package:purrr':
##
##     lift
```

```
if(!require(rpart.plot)) install.packages("rpart.plot", repos = "http://cran.us.r-project.org")
```

```
## Loading required package: rpart.plot
```

```
## Warning: package 'rpart.plot' was built under R version 4.1.3
```

```
if(!require(e1071)) install.packages("e1071", repos = "http://cran.us.r-project.org")
```

```
## Loading required package: e1071
```

```
## Warning: package 'e1071' was built under R version 4.1.3
```

```
library(tidyverse)
library(ggplot2)
library(caret)
library(dplyr)
library(corrplot)
library(randomForest)
library(rpart)
library(rpart.plot)
library(e1071)
```

Download the dataset

Since Kaggle does not allow us to download the files directly , have downloaded the file to my github and here is the link to the file:

https://github.com/rrao2511/CYO-Harvard-Capstone-Project/raw/main/housing.csv (https://github.com/rrao2511/CYO-Harvard-Capstone-Project/raw/main/housing.csv)

Reading the data from the csv file

```
boston_housing<-read.csv("https://github.com/rrao2511/CYO-Harvard-Capstone-Project/raw/main/hous
ing.csv",header=TRUE,sep=",",quote ="\"")
```

For the purpose of this analysis we are looking at a subset of the Boston housing set

First lets look at the data set - checking the dimension.

This dataset has 489 observations and 4 columns. This is a subset of the original Kaggle dataset.

There are 4 columns and the details of the column are shown below.We will be using all the 4 columns for our analysis.

We will also look at the structure of the dataset, head and the summary.

Explanation of Column names and details

RM - Average number of rooms per dwelling

LSTAT - % lower status of population

PT Ratio - Pupil teacher ratio by town

MEDV - Median Value of owner occupied homes in $1000s.

```
dim(boston_housing)
```

```
## [1] 489   4
```

```
str(boston_housing)
```

```
## 'data.frame':    489 obs. of  4 variables:
##  $ RM     : num  6.58 6.42 7.18 7 7.15 ...
##  $ LSTAT  : num  4.98 9.14 4.03 2.94 5.33 ...
##  $ PTRATIO: num  15.3 17.8 17.8 18.7 18.7 18.7 15.2 15.2 15.2 15.2 ...
##  $ MEDV   : num  504000 453600 728700 701400 760200 ...
```

```
head(boston_housing)
```

	RM <dbl>	LSTAT <dbl>	PTRATIO <dbl>	MEDV <dbl>
1	6.575	4.98	15.3	504000
2	6.421	9.14	17.8	453600
3	7.185	4.03	17.8	728700
4	6.998	2.94	18.7	701400
5	7.147	5.33	18.7	760200
6	6.430	5.21	18.7	602700

6 rows

```
summary(boston_housing)
```

```
##        RM            LSTAT          PTRATIO           MEDV        
##  Min.   :3.561   Min.   : 1.98   Min.   :12.60   Min.   : 105000  
##  1st Qu.:5.880   1st Qu.: 7.37   1st Qu.:17.40   1st Qu.: 350700  
##  Median :6.185   Median :11.69   Median :19.10   Median : 438900  
##  Mean   :6.240   Mean   :12.94   Mean   :18.52   Mean   : 454343  
##  3rd Qu.:6.575   3rd Qu.:17.12   3rd Qu.:20.20   3rd Qu.: 518700  
##  Max.   :8.398   Max.   :37.97   Max.   :22.00   Max.   :1024800
```

Cleaning up the data

Since this dataset is already clean, data cleaning was not needed and it could be used directly for analysis.

Check to see if there are duplicate values and also any missing values.

```
sum(duplicated(boston_housing))
```

```
## [1] 0
```

```
sum(is.na(boston_housing))
```

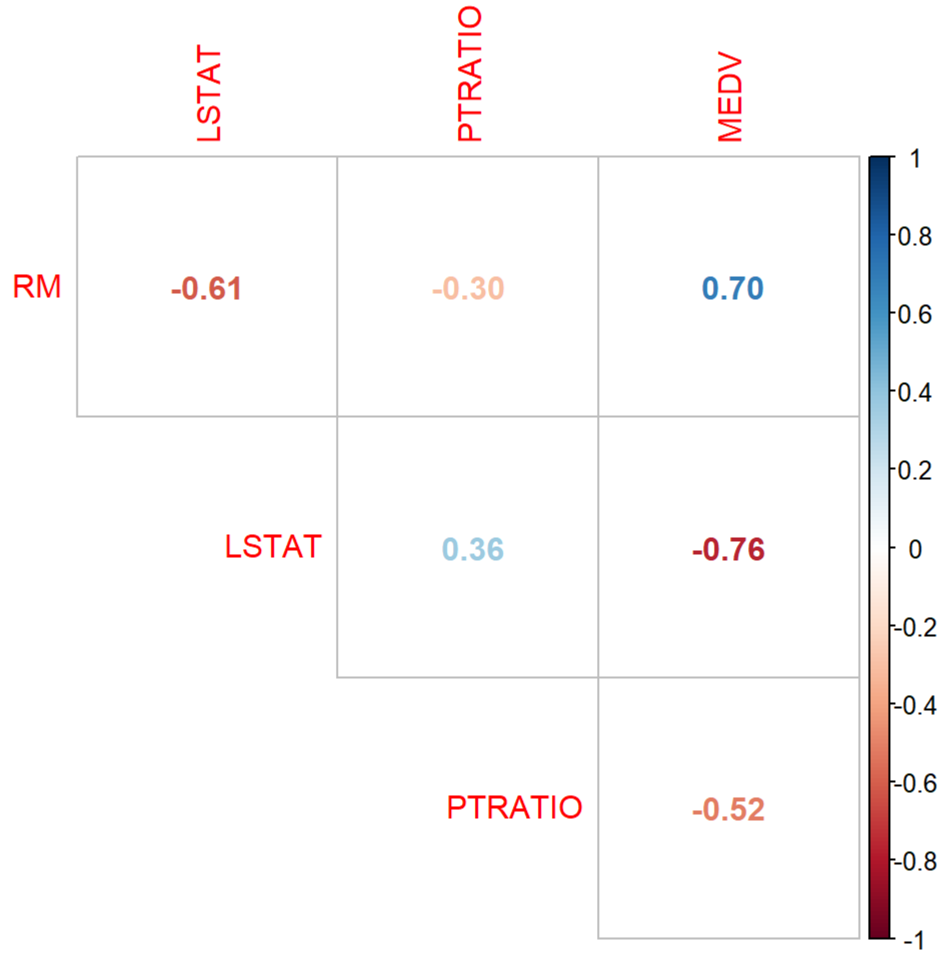
```
## [1] 0
```

3. Exploratory Data Analysis using Data Visualization

Before we start building the model we will understand the data set by doing some Exploratory Data Analysis.

Check the correlation between variables by plotting a correlation graph

```
corrplot(cor(boston_housing), method = "number", type = "upper", diag = FALSE)
```



From

From the above correlation matrix, we observe that:

Both RM and LSTAT have a strong correlation with MEDV.

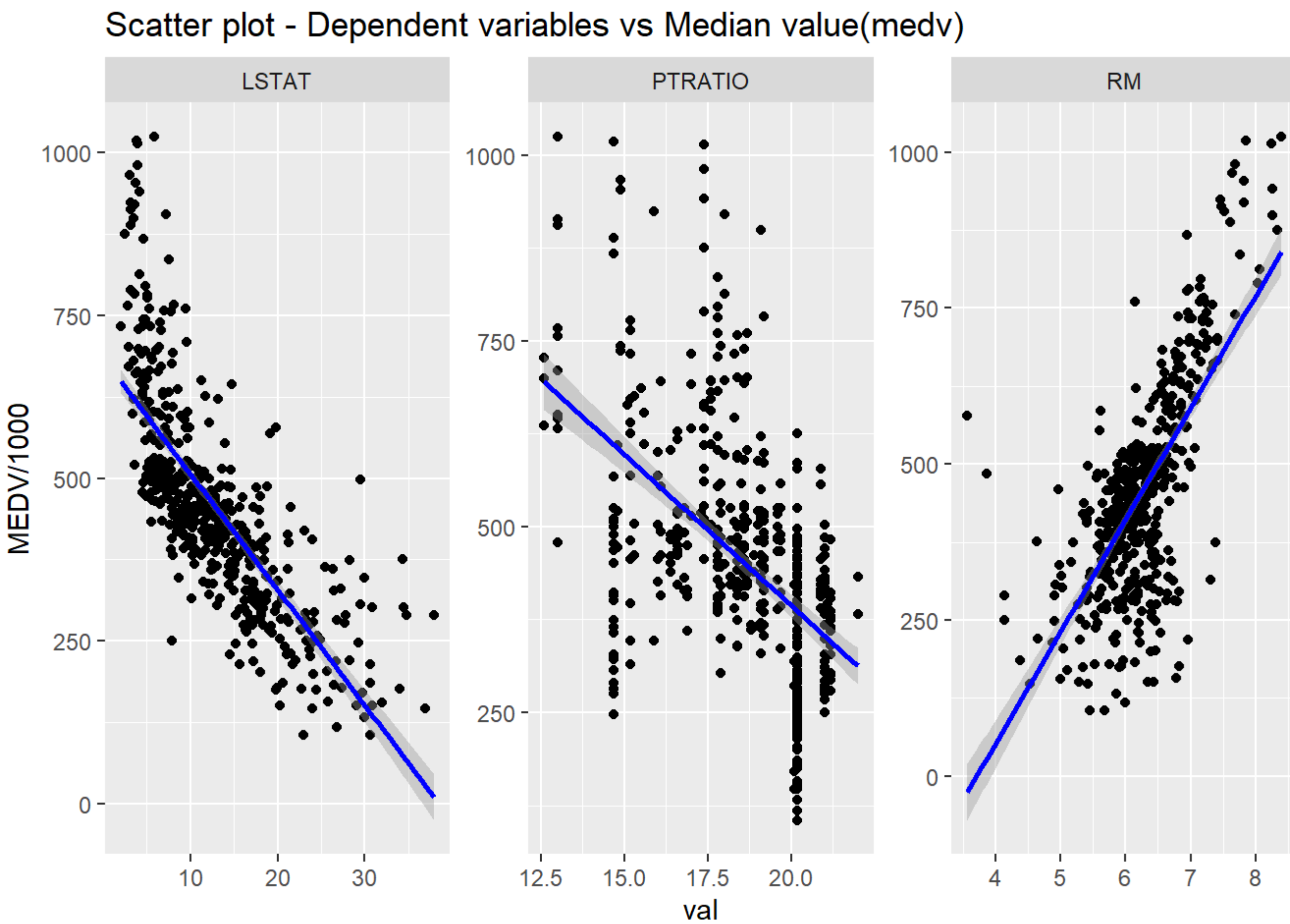
Median value of owner-occupied homes (in 1000$) increases as average number of rooms per dwelling increases and it decreases if percent of lower status population in the area increases.

PT Ratio has a positive correlation with LSTAT

Next lets look at Scatter plots to show relationship between Median value and variables

```
boston_housing%>%
  gather(key, val,-MEDV) %>%
  ggplot(aes(x = val, y = MEDV/1000))+
  geom_point()+
  stat_smooth(method = "lm", se = TRUE, col ="blue") +
  facet_wrap(~key, scales = "free")+
  theme_grey()+
  ggtitle("Scatter plot - Dependent variables vs Median value(medv)")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



From the plots we see that RM and LSTAT have a strong correlation with Median value.

The Median value prices increases as the RM value increases linearly.

The Median value prices tend to decrease with an increase in LSTAT.

4. Developing the Models

We will use three different models for this project:

Decision trees, Random Forest and Support Vector Machine.

We will evaluate the models using Root Mean Squared Error (RMSE).

First we need to split the data into train sets and test sets:

Data is split into train and test sets - 80:20

```
set.seed(123)
bh_index<- sample(nrow(boston_housing),nrow(boston_housing)*.80)
bh_train<- boston_housing[bh_index,]
bh_test<- boston_housing[-bh_index,]
```

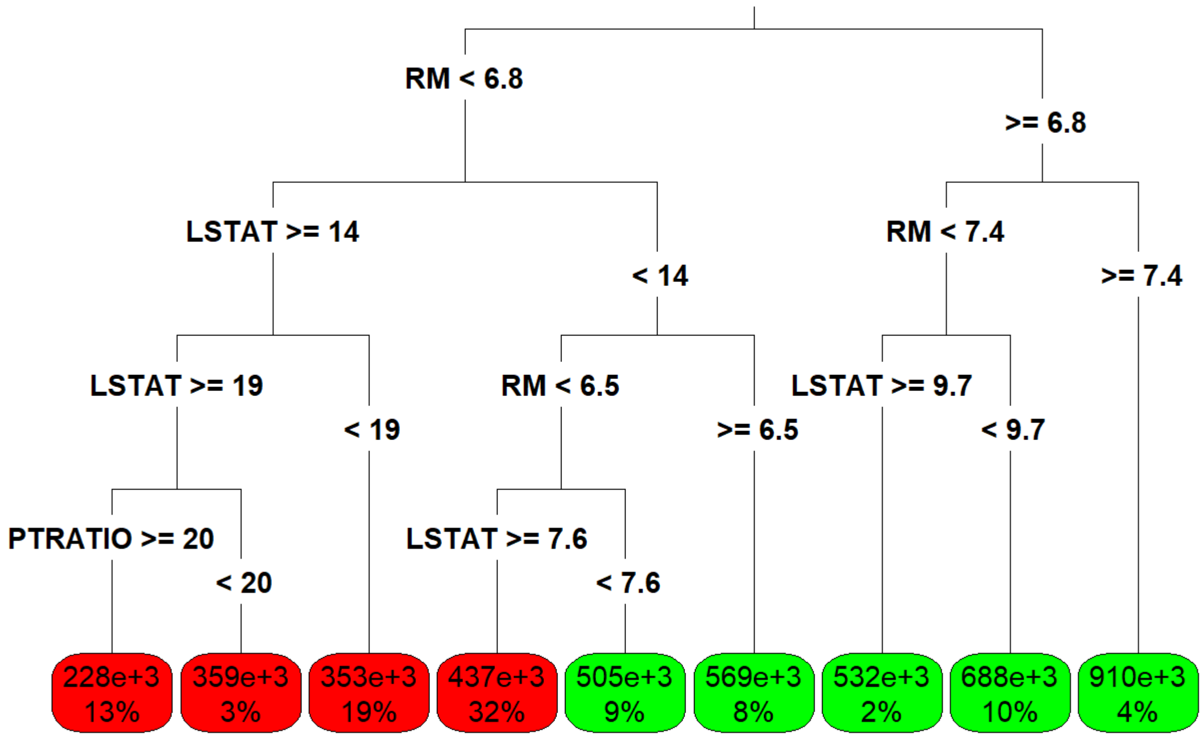
Model 1 - Decision trees

Steps - we will create the model using Decision trees on the train set, plot the decision tree, validate on the test set

and finally calculate the RMSE.

```
bhtree.fit<- rpart(MEDV~., data= bh_train)

rpart.plot(bhtree.fit, type = 3, box.palette = c("red", "green"), fallen.leaves = TRUE)
```




```
tree.pred<- predict(bhtree.fit, newdata = bh_test)

tree.rmse<- sqrt(mean((bh_test$MEDV- tree.pred)^2))

cat("Decision Tree RMSE", round(tree.rmse,2),"\n")
```

```
## Decision Tree RMSE 79926.41
```

Model 2 - Random Forest

Steps - we will create the model using Random forest on train set, validate on the test

set and finally calculate the RMSE.

```
rf.fit<- randomForest(MEDV~., data= bh_train, ntree= 500, mtry = 3)

rf.pred<- predict(rf.fit, newdata = bh_test)

rf.rmse<- sqrt(mean((bh_test$MEDV - rf.pred)^2))


cat("Random Forest RMSE", round(rf.rmse,2), "\n")
```

```
## Random Forest RMSE 71804.79
```

Model 3 - Support Vector Machines (SVM)

Steps - we will create the model using SVM on train set, validate on the test set

and finally calculate the RMSE.

```
svm.fit<- svm(MEDV~., data = bh_train, kernel= "linear", cost =1)

svm.pred<- predict(svm.fit, newdata = bh_test)

svm.rmse<- sqrt(mean((svm.pred- bh_test$MEDV)^2))


cat("SVM RMSE:", svm.rmse, "\n")
```

```
## SVM RMSE: 93155.68
```

5. Conclusion

Create a table for the RMSE values of Decision trees, Random Forest and SVM

```
results_table<- data.frame(Model = c("Decision Tree", "Random Forest", "SVM"),
                           RMSE= c(tree.rmse,rf.rmse,svm.rmse ))
```

Based on the above results here are our observations:

a. The random forest model has the lowest RMSE value of 71805, indicating that it may be the best model for predicting the median value of owner-occupied homes in Boston.
b. Whereas the Decision tree and the SVM models have higher RMSE values of 79926 & 93156 respectively indicating that they may not be the best choice for predicting the median value of owner occupied homes.

6. Limitations of the Model

We need to be cautious we need to be cautious when drawing conclusions based on RMSE values alone, as there may be other factors to consider such as model complexity, interoperability, and computational efficiency

Random forest models can be further improved with hyperparameters tuning.

But on account of shortage of time this was not attempted.

Similarly the SVM model could be tuned further by changing the parameters and the kernel function.

But on account of shortage of time this was not attempted.

7. References

https://www.kaggle.com/datasets/schirmerchad/bostonhoustingmlnd/download?datasetVersionNumber=1

https://towardsdatascience.com/things-you-didnt-know-about-the-boston-housing-dataset-2e87a6f960e8

https://github.com/tbaskaran/edX-Capstone-CYO-Project