HarvardX - CYO London Housing Prices

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1 Introduction

This report is part of "Create Your Own" project for the capstone course of Harvardx Data Science Professional Certificate.

The objective of this project is to compare the performance of selected machine learning algorithms for housing price prediction and determine whether the inclusion of demographic data (population, unemployment rate and crime rate) can improve the accuracy of the housing price prediction.

Residual mean squared error (RMSE) score is used as the performance indicator for the different algorithms and it is computed by using the formula below:

$$RMSE = \sqrt{\frac{1}{N}\sum(y_t - \hat{y}_p)^2}$$

Being:
N = number of samples
$\hat{y}_p$ = predicted value
y_t = target value

```
RMSE <- function(true_ratings, predicted_ratings){
    sqrt(mean((true_ratings - predicted_ratings)^2))
  }
```

This report is divided into the following sections: 1 Introduction 2 London Housing Data-set 3 Data Exploration 4 Model Analysis 5 Results 6 Conclusion 7 Reference

2 London Housing Prices Data Set

This project uses the housing prices data in London for the algorithms and the data was originally downloaded from Kaggle (https://www.kaggle.com/arnavkulkarni/housing-prices-in-london) and subsequently uploaded to Github. Additional demographic data is downloaded from London Data Store (https://data.london.gov.uk).

After downloaded the data, the following process is performed to prepare the data-set for the machine learning models:

- Verify and add the borough data using PostcodesioR package
- Calculate price per square foot (ppsf), unemployment rate and crime rate
- Combine housing data with demographic data
- Simplify property types
- Change the data to appropriate classes
- Tidy up the data-set and remove un-needed data
- Name the data-set "london"

```
# Load Packages
if(!require(tidyverse)) install.packages("tidyverse", repos = "http://cran.us.r-project.org")
if(!require(caret)) install.packages("caret", repos = "http://cran.us.r-project.org")
if(!require(data.table)) install.packages("data.table", repos = "http://cran.us.r-project.org")
if(!require(dplyr)) install.packages("data.table", repos = "http://cran.us.r-project.org")
if(!require(rpart)) install.packages("rpart", repos = "http://cran.us.r-project.org")
if(!require(rpart.plot)) install.packages("rpart.plot", repos = "http://cran.us.r-project.org")
if(!require(randomForest)) install.packages("randomForest", repos = "http://cran.us.r-project.
if(!require(PostcodesioR)) install.packages("PostcodesioR", repos = "http://cran.us.r-project.
if(!require(corrplot)) install.packages("corrplot", repos = "http://cran.us.r-project.org")
if(!require(readxl)) install.packages("readxl", repos = "http://cran.us.r-project.org")

# Download London housing dataset
dl <- tempfile()
download.file("https://github.com/tobwon/CYO/raw/main/London.csv.zip", dl)
data<-unz(dl, "London.csv")
data<-read.csv(data, header = TRUE, sep = ",")
data<-as.data.frame(data)
rm(dl)

# Add borough data and verify location of properties to by using postcode with PostcodesioR pa
# This will take some time and internet connection is needed
x<-1:3480
geo_info<-sapply(x, function(n){
  postcode_lookup(as.character(data[n,11]))
             })
geo_info<-as.data.frame(t(geo_info))

# Tidy up the London housing data-set and convert the varibles to appropriate types
temp_data<-data%>%
  mutate(price=as.numeric(Price),
         type=as.factor(House.Type),
         area=as.numeric(Area.in.sq.ft),
         bedroom=as.numeric(No..of.Bedrooms),
         bathroom=as.numeric(No..of.Bathrooms),
         reception=as.numeric(No..of.Receptions),
         ID = row_number())%>%
  select(ID, price, type, area, bedroom, bathroom, reception)

# Tidy up the postcode data-set and convert the varibles to appropriate types
```

```r
temp_info<-as.data.frame(geo_info)%>%
  mutate(postcode=as.character(postcode),
         region=as.character(region),
         borough=as.character(admin_district),
         ID = row_number())%>%
  select(ID, postcode, region, borough)

# Tidy up the data-set by removing properties not in London and simplify the property types to
london <- left_join(temp_data, temp_info, by="ID")%>%
  filter(str_detect(region, "London"))
london$type<-str_replace_all(london$type, c("New development"="Apartment", "Flat / Apartment"="

# Convert to price per square feet
london <- london%>%mutate(ppsf=price/area)

# Download London unemployment data
temp = tempfile(fileext = ".xlsx")
download.file("https://data.london.gov.uk/download/employment-rates-by-ethnicity/cf8a5d62-6918-

# Remove un-needed data and tidy up the unemployment data-set
data3 <- read_xlsx(temp, sheet=4)
data3 <-as.data.frame(data3)
london_unemployment<-data3[-c(1:3, 36:57), c(2, 3, 4, 7, 8, 11, 12, 15, 16, 19, 20, 23, 24, 27
london_unemployment[london_unemployment == "!"] <- "0"
london_unemployment[london_unemployment == "#"] <- "0"
london_unemployment[, c(2:15)] <- sapply(london_unemployment[, c(2:15)], as.numeric)

# Replace City of London with Hackeny
london$borough<-str_replace_all(london$borough, c("City of London"="Hackney"))

# Calculate the unemployment rate in different boroughs
london_unemployment$population<-london_unemployment$...4+london_unemployment$...8+london_unempl
london_unemployment$employment<-london_unemployment$`working age employment rate - white`+londo
london_unemployment$unemployment<-london_unemployment$population-london_unemployment$employment
london_unemployment$unemployment_rate<-london_unemployment$unemployment/london_unemployment$pop
london_unemployment<-london_unemployment%>%rename(borough=...2)%>%select(borough, population, u

# Download London crime data
data2 <- read.csv("https://data.london.gov.uk/download/recorded_crime_summary/d2e9ccfc-a054-41

# Tidy up the London crime data-set
data2 <- as.data.frame(data2)
london_crime<-data2%>%mutate(sum=rowSums(.[4:27]))%>%select(c("LookUp_BoroughName", "sum"))%>%g

# Combine London un-employment and crime data-sets
london_e_c<-left_join(london_crime, london_unemployment, by="borough")
```

```r
# Calculate crime rate in different boroughs
london_e_c<-london_e_c%>%mutate(crime_rate=crime/population)%>%select(c("borough", "population"

# Add population, unemployment rate, and crime rate to "London" data-set
london <-left_join(london, london_e_c, by="borough")
london$borough<-as.factor(london$borough)

# Remove un-needed columns
london<-subset(london, select=c(-ID, -region, -postcode, -price))

# Rearrange columns to put ppsf as the first column
london<-london[,c(7,1,2,3,4,5,6,8,9,10)]

# Remove temporary files
rm(temp_data, temp_info, x, london_e_c, london_crime, london_unemployment)
```

3 Data Exploration

Before building the machine learning models, data exploration is carried out on "london" data-set to understand the data structure and the variables it contained. This process helps to determine how the models is built for the analysis.

```r
# Summary of "london" data-set
summary(london)
```

```
      ppsf              type           area          bedroom      bathroom
 Min.   : 242   Apartment:1872   Min.   :  274   Min.   : 0   Min.   : 0
 1st Qu.: 763   House    :1251   1st Qu.:  816   1st Qu.: 2   1st Qu.: 2
 Median : 935   Penthouse:  96   Median : 1250   Median : 3   Median : 3
 Mean   :1102                   Mean   : 1601   Mean   : 3   Mean   : 3
 3rd Qu.:1250                   3rd Qu.: 2062   3rd Qu.: 4   3rd Qu.: 4
 Max.   :7069                   Max.   :14358   Max.   :10   Max.   :10

   reception                     borough       population     unemployment_rate
 Min.   : 0   Wandsworth            : 676   Min.   :133000   Min.   :0.16
 1st Qu.: 2   Westminster           : 441   1st Qu.:181600   1st Qu.:0.23
 Median : 3   Kensington and Chelsea: 297   Median :262400   Median :0.26
 Mean   : 3   Hammersmith and Fulham: 247   Mean   :240488   Mean   :0.26
 3rd Qu.: 4   Islington             : 227   3rd Qu.:283300   3rd Qu.:0.31
 Max.   :10   Richmond upon Thames  : 227   Max.   :383400   Max.   :0.35
              (Other)               :1104
   crime_rate
 Min.   :0.13
 1st Qu.:0.18
 Median :0.20
```

```
 Mean   :0.25
 3rd Qu.:0.25
 Max.   :0.48
```

From the summary above, it is noted that "london" data-set a data.frame and it contains 10 columns/variables and 3219 rows/observations. The columns in "london" are:

- "ppsf" - price per square foot
- "type" - property type ("apartment", "house" and "penthouse")
- "area" - size of the property
- "bedroom" - number of bedroom
- "bathroom" - number of bathroom
- "reception" - number of reception
- "borough" - the borough which the property is located
- "population" - population of the borough
- "unemployment_rate" - unemployment rate of the borough
- "crime_rate" - crime rate of the borough

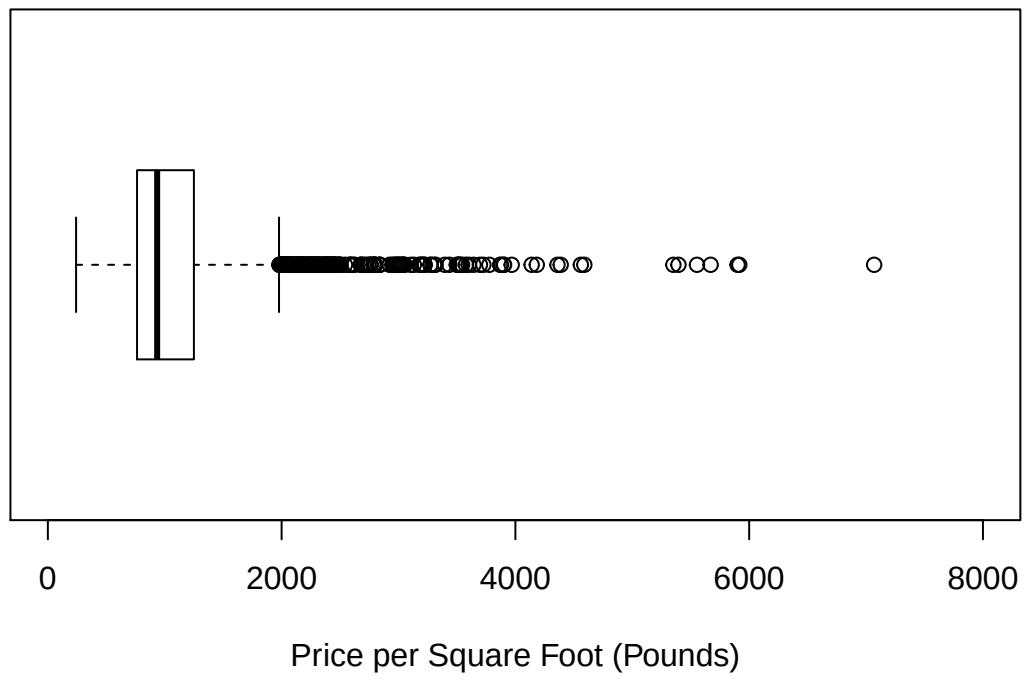
```r
# Display the first 6 rows of "london"
head(london)
```

```
  ppsf      type area bedroom bathroom reception     borough population
1  617     House 2716       5        5         5      Merton     181600
2  799 Apartment  814       2        2         2   Islington     222300
3  966 Apartment  761       2        2         2  Wandsworth     283300
4  889     House 1986       4        4         4  Wandsworth     283300
5  964 Apartment  700       2        2         2  Wandsworth     283300
6 1042 Apartment  403       1        1         1 Westminster     233200
  unemployment_rate crime_rate
1              0.23       0.15
2              0.26       0.24
3              0.16       0.18
4              0.16       0.18
5              0.16       0.18
6              0.35       0.48
```

The first 6 rows shown that all variables are in numeric class except "type" and "borough", which are in factor class.

The most important variable in the data-set is price per square foot (ppsf) and the algorithms in the project are constructed to predict ppsf. By using ppsf, the prediction takes away the factor of the size of the property to provide a more accurate reflection of the property price.

```r
# Boxplot of ppsf
boxplot(london$ppsf, horizontal = TRUE, xlab = "Price per Square Foot (Pounds)", main = "PRICE
```



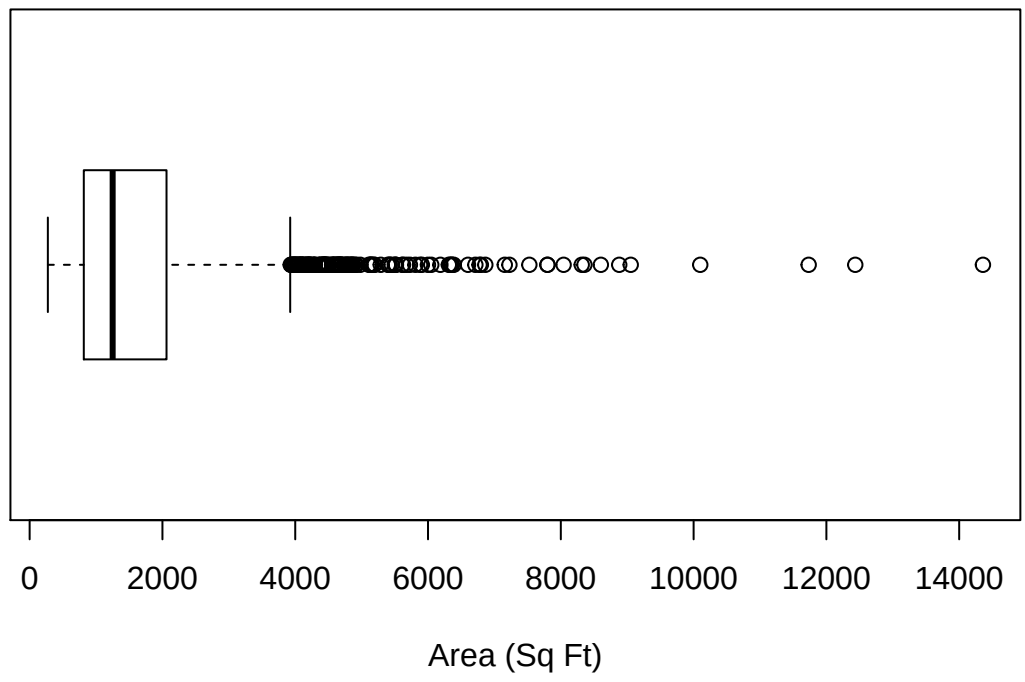
The ppsf boxplot above shown a range from GBP 241.61 per sq ft to GBP 7069.18 per sq ft and it also shown majority of the property is around GBP 1000 per sq ft.

```
# Types of property
london%>%group_by(type) %>%
  summarize(count = n(), .groups='drop') %>%
  arrange(desc(count))
```

```
# A tibble: 3 x 2
  type      count
  <fct>     <int>
1 Apartment  1872
2 House      1251
3 Penthouse    96
```

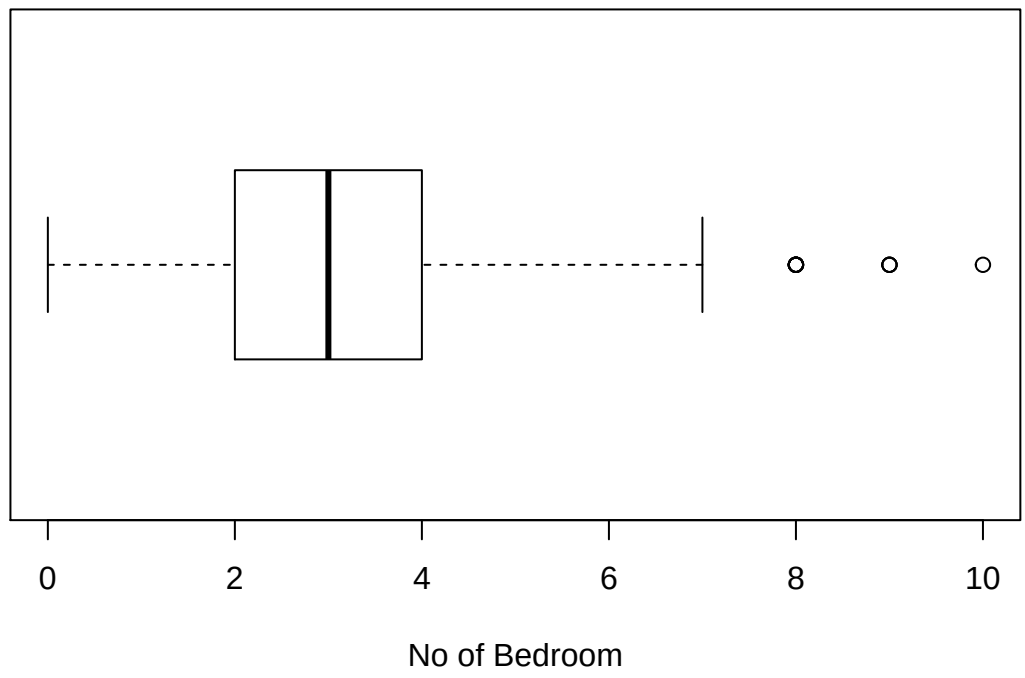
The properties are sorted into three different types as shown in the table above. “Apartment” and “House” are the two predominant types while much lesser properties are “Penthouse”.

```
# Size of Properties Boxplot
boxplot(london$area, horizontal = TRUE, main = "SIZE OF PROPERTIES", xlab = "Area (Sq Ft)")
```



As shown in the size of properties boxplot above, majority of the property is less than 2000 sq ft. The range of the property size is from 274 sq ft to 14358 sq ft.

```
# Bedroom Boxplot
boxplot(london$bedroom, horizontal = TRUE, main = "BEDROOM NUMBER", xlab = "No of Bedroom")
```



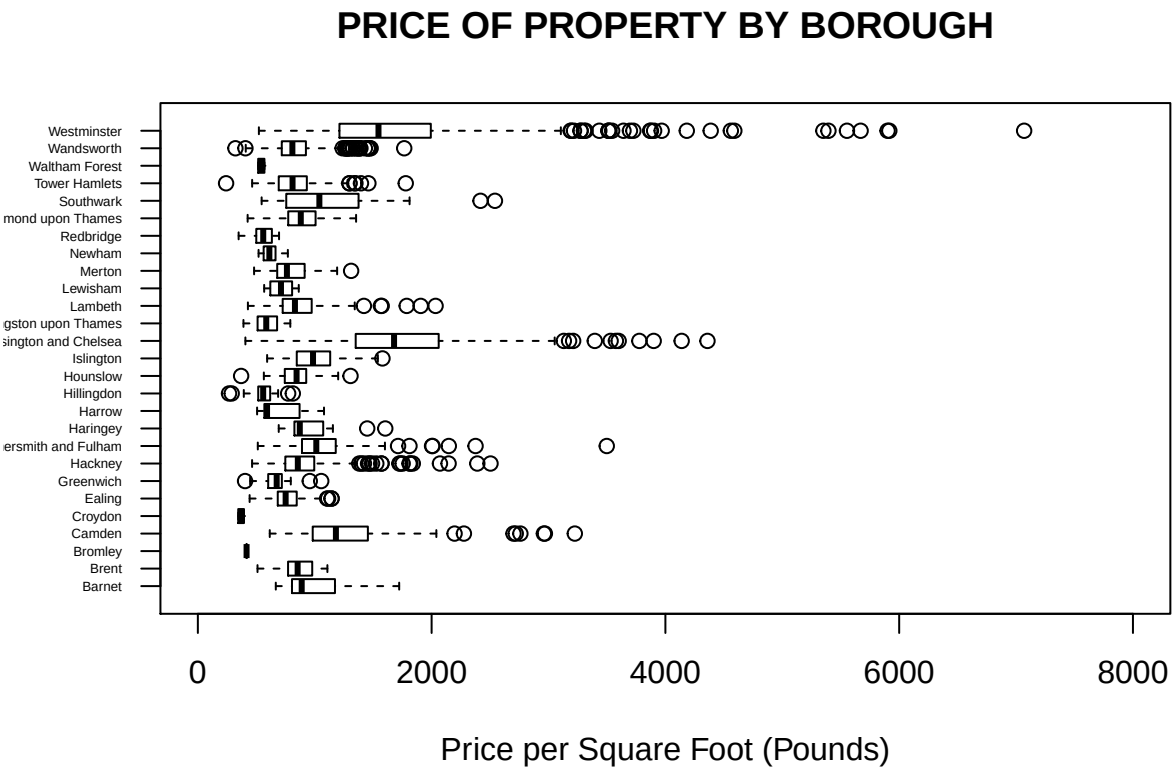
The bedroom boxplot demonstrated that majority of the properties have two to four bedrooms and the maximum bedroom number is ten, minimum is zero.

```
# Property Transactions in Different Boroughs
london%>%group_by(borough) %>%
  summarize(count = n(), .groups='drop') %>%
  arrange(desc(count))
```

```
# A tibble: 27 x 2
   borough                count
   <fct>                  <int>
 1 Wandsworth               676
 2 Westminster              441
 3 Kensington and Chelsea   297
 4 Hammersmith and Fulham   247
 5 Islington                227
 6 Richmond upon Thames     227
 7 Camden                   180
 8 Hackney                  165
 9 Tower Hamlets            156
10 Lambeth                  121
# ... with 17 more rows
```

The properties in the data-set is located in 27 different boroughs. “Wandsworth” has most of the property transactions while “Bromley” has only one.

```
# ppsf of Property by Borough
boxplot(london$ppsf ~ london$borough, horizontal = TRUE,  ylab= NULL, xlab = "Price per Square
axis(1,cex.axis=1)
```



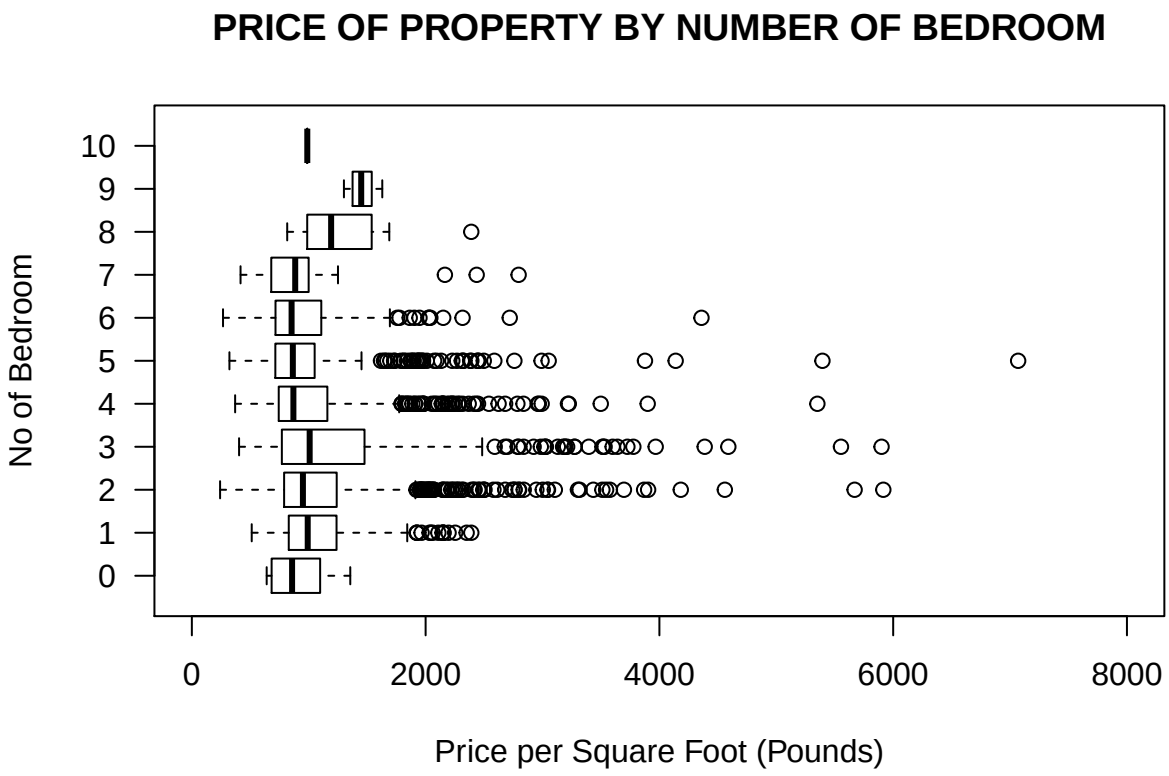
The above boxplot shown ppsf in different boroughs and properties located in “Westminster” and “Kensington and Chelsea” generally have higher prices.

It also shown the highest priced property is located in “Westminster” and the borough which has the lowest priced property is “Tower Hamlets”.

```
# ppsf by Property Type
boxplot(london$ppsf ~ london$type, horizontal = TRUE, ylab = NULL, xlab = "Price per Square Fo
```

The boxplot above shown ppsf with different property types. "Penthouse" and "Apartment" are generally more expensive than "House". "Apartment" has a wide range as it has the most expensive property as well as the least expensive one.

```
# ppsf by Number of Bedroom
boxplot(london$ppsf ~ london$bedroom, horizontal = TRUE, ylab = "No of Bedroom", xlab = "Price
```



The price by number of bedroom boxplot above shown majority of the property prices are not affected by the number of bedroom. It is also noted that the highest priced property has five bedrooms and more bedrooms not neccessarily increase the property price.

```
# Population in different boroughs
temp<-london%>%select(borough, population)%>%distinct()
temp[order(temp$population),]
```

```
                borough population
6  Kensington and Chelsea     133000
11   Kingston upon Thames     147500
9    Richmond upon Thames     151100
5  Hammersmith and Fulham     160300
1                  Merton     181600
2               Islington     222300
4             Westminster     233200
23                 Harrow     242100
7                Haringey     242400
26         Waltham Forest     243700
27                Bromley     257900
8                  Camden     262400
12               Hounslow     266600
17              Greenwich     280800
```

```
3              Wandsworth     283300
13                Hackney     285300
21              Lewisham      296600
14             Hillingdon     303700
10                Lambeth     315000
18              Redbridge     316100
20              Southwark     321200
15          Tower Hamlets     332600
22                Croydon     341300
16                 Ealing     342200
19                 Barnet     343200
25                  Brent     358400
24                 Newham     383400
```

```
rm(temp)
```

The borough which has the lowest population is "Kensington and Chelsea" while the borough which has the highest population is "Newham". The population does not seem to correspond to the property prices.

```
# Unemployment Rate in Different Boroughs
temp<-london%>%select(borough, unemployment_rate)%>%distinct()
temp[order(temp$unemployment_rate),]
```

```
                 borough unemployment_rate
3              Wandsworth              0.16
1                  Merton              0.23
9    Richmond upon Thames              0.23
27                Bromley              0.23
21              Lewisham              0.23
11   Kingston upon Thames              0.24
20              Southwark              0.24
17              Greenwich              0.24
10                Lambeth              0.25
22                Croydon              0.25
14             Hillingdon              0.25
2               Islington              0.26
5  Hammersmith and Fulham              0.26
7                Haringey              0.26
19                 Barnet              0.26
12              Hounslow              0.26
16                 Ealing              0.27
18              Redbridge              0.27
24                 Newham              0.29
23                 Harrow              0.29
15          Tower Hamlets              0.30
13                Hackney              0.30
```

```
26         Waltham Forest              0.31
6  Kensington and Chelsea              0.31
25                 Brent              0.31
8                 Camden              0.34
4            Westminster              0.35
```

```
rm(temp)
```

The borough which has the lowest unemployment rate is "Wandsworth" and the borough which has the highest unemployment rate is "Westminster". The unemployment rates also do not seem to correspond with the property prices.

```
# Crime Rate in Different Boroughs
temp<-london%>%select(borough, crime_rate)%>%distinct()
temp[order(temp$crime_rate),]
```

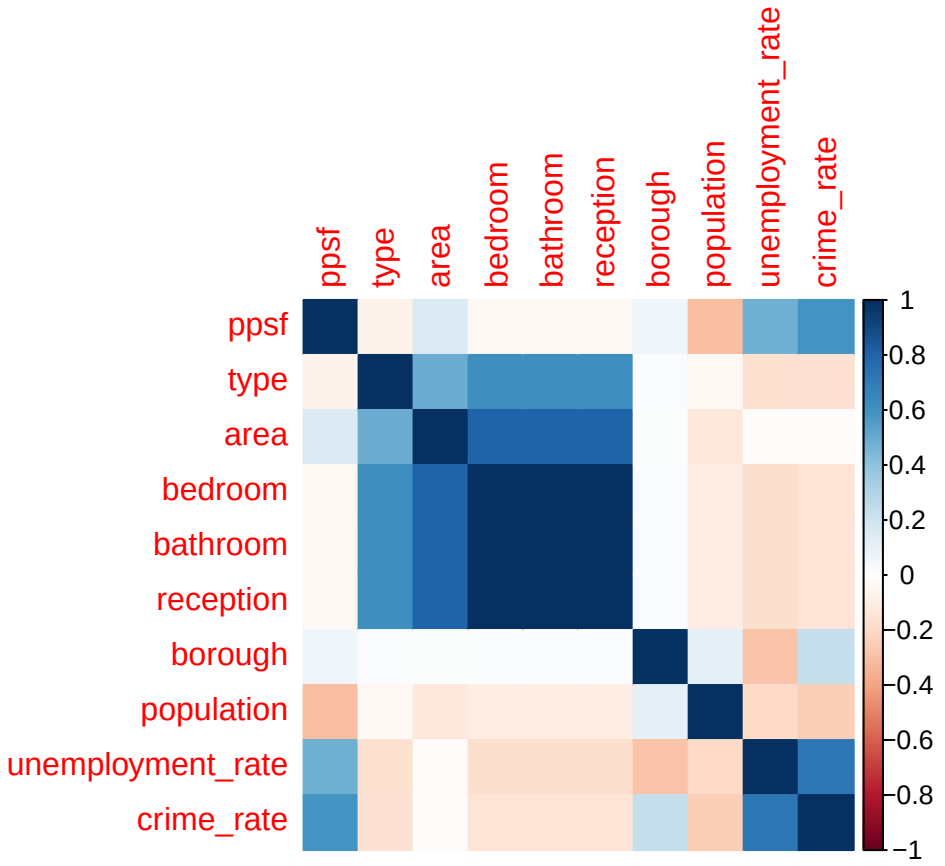
```
                 borough crime_rate
23                Harrow       0.13
18             Redbridge       0.15
1                 Merton       0.15
11  Kingston upon Thames       0.16
25                 Brent       0.16
9   Richmond upon Thames       0.16
19                Barnet       0.17
14            Hillingdon       0.17
16                Ealing       0.17
24                Newham       0.18
27               Bromley       0.18
3             Wandsworth       0.18
12              Hounslow       0.19
21              Lewisham       0.19
17             Greenwich       0.19
26        Waltham Forest       0.19
22               Croydon       0.19
15         Tower Hamlets       0.20
10               Lambeth       0.20
20             Southwark       0.21
13              Hackney       0.22
2              Islington       0.24
8                 Camden       0.24
7                Haringey       0.24
5  Hammersmith and Fulham       0.25
6  Kensington and Chelsea       0.30
4            Westminster       0.48
```

```
rm(temp)
```

The borough which has the lowest crime rate is "Harrow" and "Westminster" has the highest crime rate. The crime rates do not correspond with the boroughs which have the highest and lowest property prices.

After inspected the variables in the "london" data-set, a correlation matrix is produced by using "corrplot" package to provide a preliminary analysis of the correlation coefficients between the different variables.

```
# Produce Correlation Matrix
london_cor<-london
london_cor$type<-as.numeric(london_cor$type)
london_cor$borough<-as.numeric(london_cor$borough)
corlondon<-cor(london_cor)
corrplot(corlondon, method="color")
```



According to the correlation matrix of "London" data-set, ppsf is positively affected by "crime rate" and "unemployment rate" followed by "area" and "borough". "Population" has negative correlation with the price while other variables, number of bedroom, bathroom and reception have no effect on ppsf.

4 Model Analysis

In order to test whether demographic data affects the property price and hence the accuracy of the prediction, the models are divided into two sets: one without the demographic data and another with the demographic data.

The models are built with the following machine learning algorithms:

A. Linear Regression B. Decision Tree C. Random Forrest

RMSE scores are computed for the two sets of models and they are compared and analysed to deduce the findings for this project.

4.1 Data Preparation

In order to verify the models, "London" data-set is split into "test_set" and "train set". "train_set" is used in the machine learning algorithms and "test_set" is used to verify the models and compute the RMSE scores. "test_set" is 10% of "london" data-set while "train_set" contains 90% of the data.

```
# Splitting "london" data-set into traning set and test set.  Test set is 10% of "london" data
set.seed(2)
test_index <- createDataPartition(london$ppsf, times = 1, p = 0.1, list = FALSE)
train_set <- london[-test_index,]
test_set <- london[test_index,]

# Remove temporary file
rm(test_index)
```

4.2 Baseline Model

After completed the process to create "train_set" and "test_set", a baseline Model is produced by calculating the average ppsf of "train_set" and its RMSE score is used as the baseline for the results.

```
##################
# Baseline Model #
##################

mu<-mean(train_set$ppsf)
rmse0<-RMSE(test_set$ppsf, mu)
```

The average ppsf is GBP 1102.65 per sq ft and it resulted a RMSE score of 518.38.

4.3 Models Without Demographic Data

The first set of models, Model 1A, 1B and 1C, are constructed without using the demographic data.

4.3.1 Model 1A Linear Regression Without Demographic Data

Model 1A is constructed using linear regression as the algorithm.

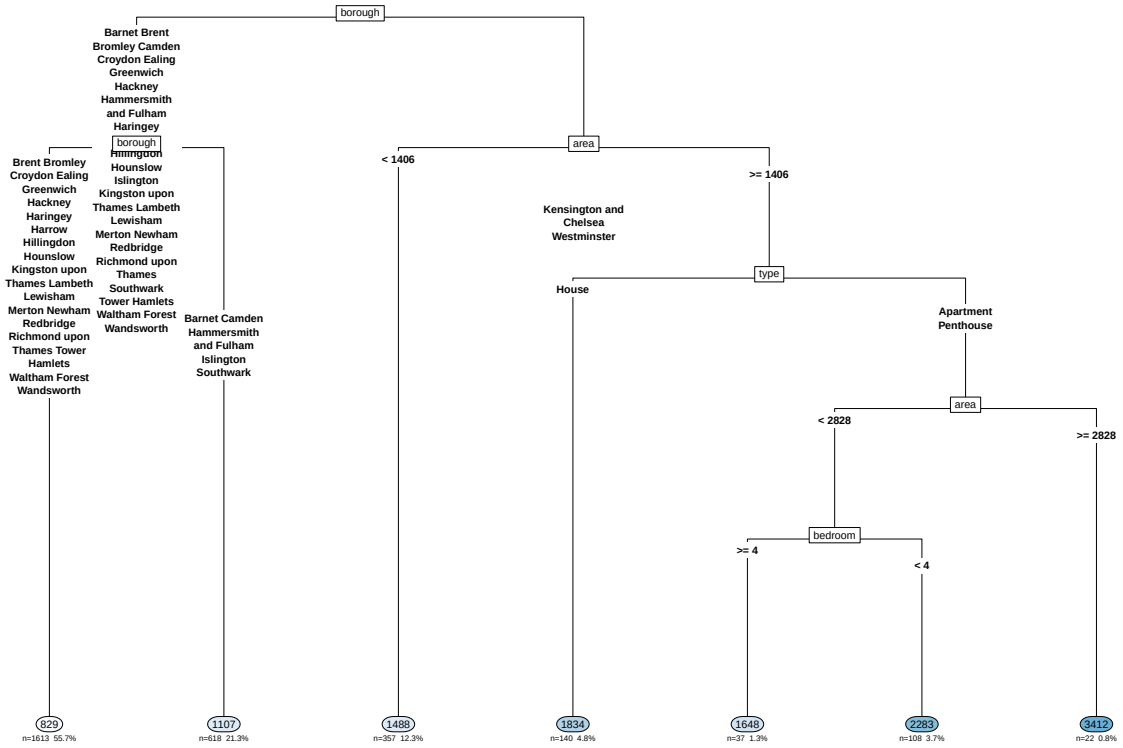
```
#########################################################
# Model 1A Linear Regression Without Demographic Data #
#########################################################

# Linear Regression Computation
lr <- lm(ppsf ~ type+area+bedroom+bathroom+reception+borough, data = train_set)
model1a <- predict(lr, newdata = test_set)

# Compute RMSE for Model 1A
rmse1a<-RMSE(test_set$ppsf, model1a)
```

The RMSE score from Model 1A is 333.3 which performed better than the baseline model as expected.

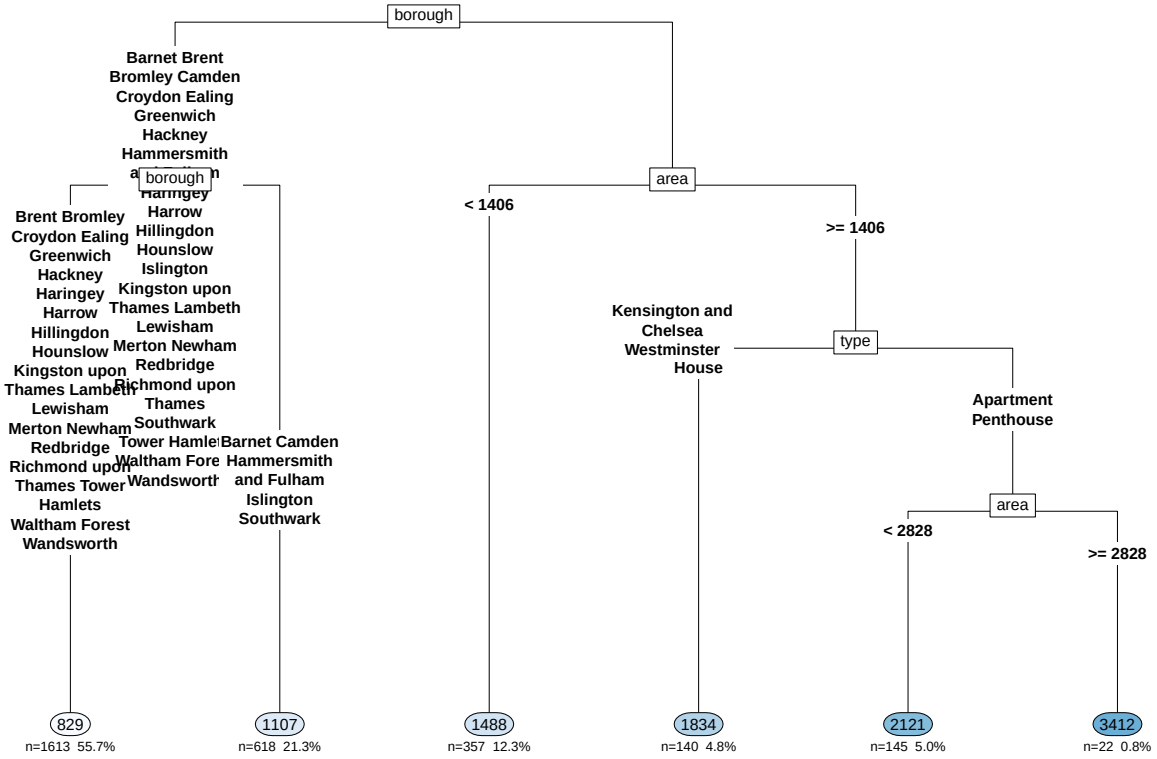
4.3.2 Model 1B Decision Tree Without Demographic Data

Model 1B uses Decision Tree as the machine learning algorithm and included pruning to try to improve the accuracy by reducing over-fitting.

```
#####################################################
# Model 1B Decision Tree Without Demographic Data #
#####################################################

# Decision Tree Computation
train_rpart1b <- rpart(ppsf ~ type+area+bedroom+bathroom+reception+borough, data = train_set)

# Split text display
split.fun <- function(x, labs, digits, varlen, faclen)
{
# replace commas with space
labs <- gsub(",", " ", labs)
for(i in 1:length(labs)) {

# split labs[i] into multiple lines
labs[i] <- paste(strwrap(labs[i], width = 15), collapse = "\n")
}
labs
}

rpart.plot(train_rpart1b, faclen = 0, type=5, yesno=T, clip.facs = TRUE, under = T, digits=-3,
```




```
# Prune the Tree
pfit1b<- prune(train_rpart1b, cp=train_rpart1b$cptable[which.min(train_rpart1b$cptable[,"xerro
rpart.plot(pfit1b, faclen = 0, type=5, yesno=T, clip.facs = TRUE, under = T, digits=-3, extra=
```




```
model1b <- predict(pfit1b, newdata=test_set)

# Compute RMSE for Model 1B
rmse1b<-RMSE(test_set$ppsf, model1b)
```

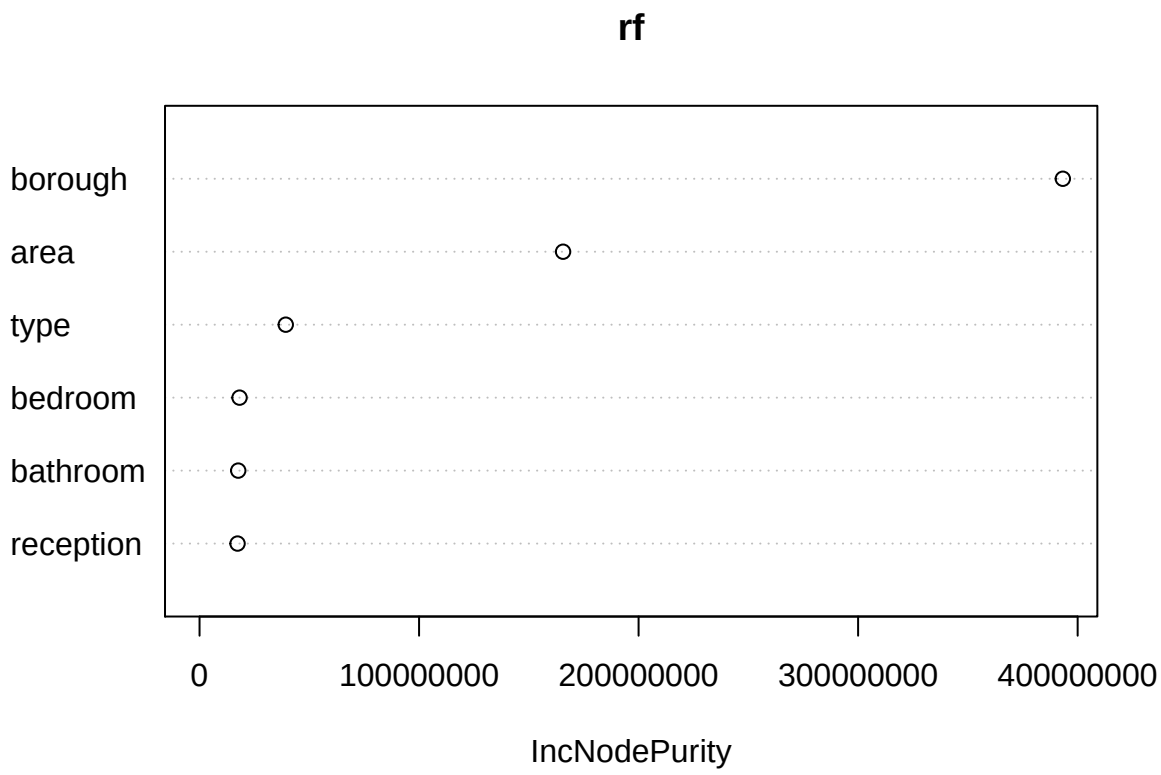
Model 1B achieved a RMSE score of 337.51 and it shown Model 1B is not as accurate as Model 1A. The resulted decision tree shown "borough" as the most significant variable followed by "area" and "type". It is also noted that bedroom is also one of the more significant variable before the pruning.

4.3.3 Model 1C Random Forest Without Demographic Data

Model 1C uses Random Forest as the machine learning algorithm.

```
#################################################################
# Model 1C Random Forest Without Demographic Data Computation #
#################################################################

# Random Forest Computation
rf<-randomForest(ppsf~type+area+bedroom+bathroom+reception+borough, data=train_set)
model1c <- predict(rf, newdata=test_set)
```

```
importance  <- importance(rf)
varImpPlot(rf)
```




```
# Compute RMSE for Model 1C
rmse1c<-RMSE(test_set$ppsf, model1c)
```

Model 1C resulted a RMSE score of 324.47. It performed better than previous models and it shown "borough" is the most significant variable followed by "area" and "type".

4.4 Model With Demographic Data

The second set of models, Model 2A, Model 2B and Model 2C, included demographic data in the machine learning algorithms.

4.4.1 Model 2A Linear Regression With Demographic Data

Model 2A, similar to Model 1A, uses linear regression as the machine learning algorithm.

```
#########################################################
# Model 2A  - Linear Regression With Demographic Data #
```

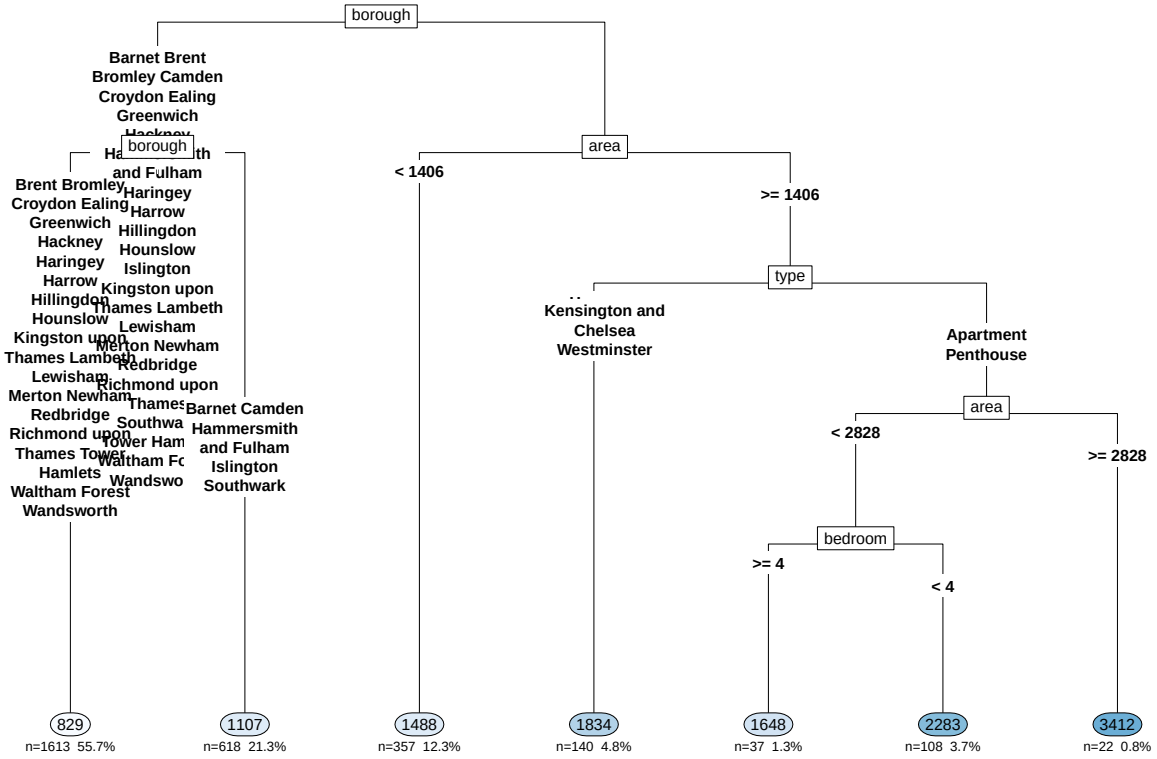
```
#########################################################

# Linear Regression Computation
lr <- lm(ppsf ~ ., data = train_set)
model2a <- predict(lr, newdata = test_set)

# Compute RMSE for Model 2A
rmse2a<-RMSE(test_set$ppsf, model2a)
```

The RMSE score from Model 2A is 333.3, which is exactly the same as Model 1A. It shown demographic data made no differece in the computation of linear regression model.

4.4.2 Model 2B Decision Tree With Demographic Data

Model 2B uses Decision Tree, with pruning, as the machine learning algorithm.

```
################################################
# Model 2B Decision Tree With Demographic Data #
################################################

# Decision Tree Computation
train_rpart2b <- rpart(ppsf ~ ., data = train_set)
rpart.plot(train_rpart2b, faclen = 0, type=5, yesno=T, clip.facs = TRUE, under = T, digits=-3,

# Prune the Tree
pfit2b<- prune(train_rpart2b, cp=train_rpart2b$cptable[which.min(train_rpart2b$cptable[,"xerro
rpart.plot(pfit2b, faclen = 0, type=5, yesno=T, clip.facs = TRUE, under = T, digits=-3, extra=
```




```
model2b <- predict(pfit2b, newdata=test_set)

# Compute RMSE for Model 2B
rmse2b<-RMSE(test_set$ppsf, model2b)
```

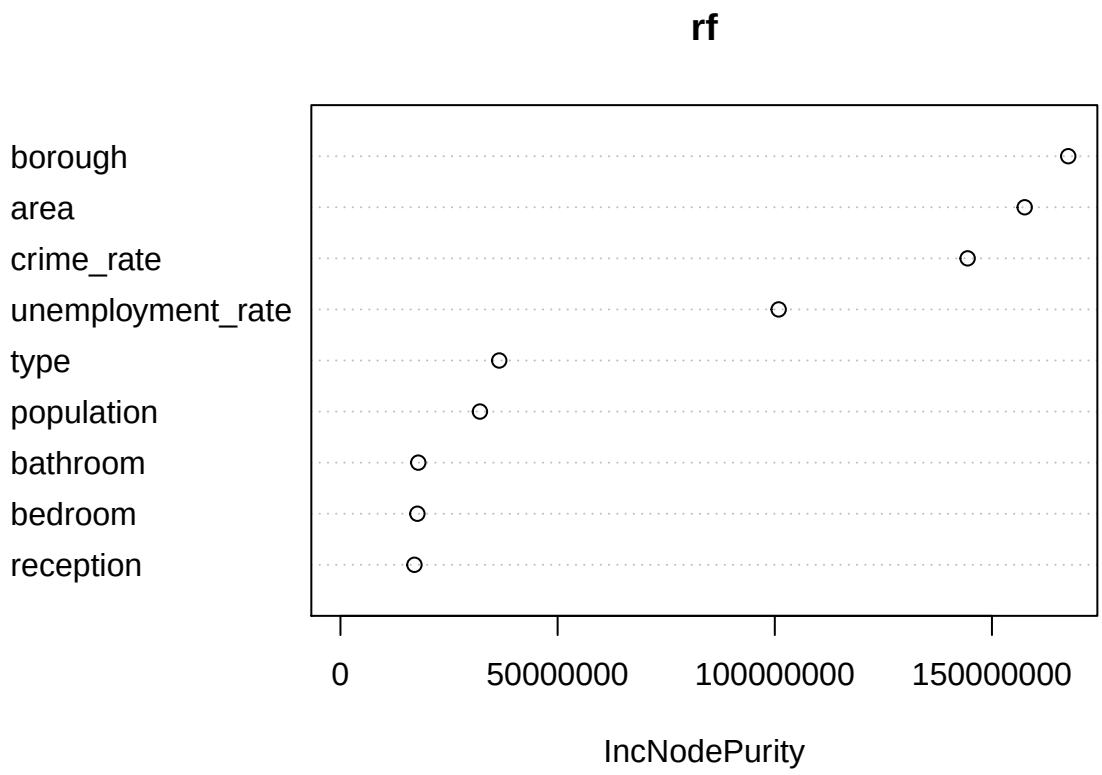
The RMSE score for Model 2B is 331.74 and it performed better than Model 1B, decision tree without demographic data. The significant variables are "borough", "area", "type" and "bedroom" which are similar to Model 1B. Although the demographic data is deemed not significant in the algorithm, it still improved the RMSE score nevertheless. It also noted that pruning made no difference in the outcome.

4.4.3 Model 2C Random Forest With Demographic Data

Model 2C uses Random Forest in the machine learning model.

```
#############################################################
# Model 1C Random Forest With Demographic Data Computation #
#############################################################

# Random Forest Computation
rf<-randomForest(ppsf~., data=train_set)
model2c <- predict(rf, newdata=test_set)
```

```
importance <- importance(rf)
varImpPlot(rf)
```




```
# Compute RMSE for Model 2C
rmse2c<-RMSE(test_set$ppsf, model2c)
```

Model 2C achieved a RMSE score of 329.1 which is the best in the models with demographic data. It shown "borough" as the most significant variable in the prediction followed by "area", "crime rate" and "unemployment rate". "population" and "type" also had reasonable effect in the algorithm.

5 Results

```
#Compile the results into a summary table
summary <- tibble(Model = c("Baseline Model", "Model 1A Linear Regression without Demographic I
summary
```

```
# A tibble: 7 x 3
  Model                                          RMSE `Difference to Baseline Mo~
```

	<chr>	<dbl>	<dbl>
1	Baseline Model	518.	0
2	Model 1A Linear Regression without Demograp~	333.	185.
3	Model 1B Decision Tree without Demographic ~	338.	181.
4	Model 1C Random Forest without Demographic ~	324.	194.
5	Model 2A Linear Regression with Demographic~	333.	185.
6	Model 2B Decision Tree with Demographic Data	332.	187.
7	Model 2C Random Forest with Demographic Data	329.	189.

The results are compiled in the summary table above and the key findings are:

- The most accurate prediction is by Model 1C Random Forest without demographic data
- Demographic data made no difference in linear regression models, Model 1A and Model 2A
- Demographic data improved the accuracy in Decision Tree model as shown in Model 2B
- Although the demographic data is shown as important variables in the random forest model - Model 2C however the Model 1C, random forest without demographic data performed better
- Borough is the most important variable across the different algorithms which confirmed the location factor contributes the most to housing price
- Despite the size factor is taken away by using ppsf, the size of property still affect the housing prices as larger properties also have higher ppsf

6 Conclusion

From the two sets of machine learning models tested, it is clear that Random Forest algorithm outperformed Linear Regression and Decision Tree in housing price prediction. It is less clearer whether the inclusion of demographic data (population, unemployment rate and crime rate) improves the performance of the algorithms as the results are varied and inconclusive.

6.1 Limitation and Future Work

This project is limited by the size of the data-set, number of variables and limited number of machine learning algorithms. The following further works can be implemented to build from this project and possibly come up with more conclusive results:

- Increase the size of the data-set used by including more transactions in London or even including transactions outside of London. This will improve the predictive power of the algorithms.
- Increase the number variables such as number of car space, proximity to education, proximity to amenities etc to study whether these factors can improve the algorithms.
- Test other demographic variables such as education level, marriage ratio, children population and average number of household etc to study whether other demographic data can affect the prediction.
- Study other machine learning algorithms, such as XGBoost which is often used in housing price prediction, to improve from random forest for the prediction

7. Reference

Rafael A. Irizarry (2019), Introduction to Data Science: Data Analysis and Prediction Algorithms with R