Pricing

2023-01-08

Realizado por : Jose Delgado Serrano (Grupo 1) GitHub: https://github.com/Josdelser/PreciosMadrid-FID
Kaggle: https://www.kaggle.com/datasets/mapecode/madrid-province-rent-data

Paquetes y librerias

```
#install.packages("tidyverse")
#install.packages("dplyr")
#install.packages("rattle")
# libraries
library(rpart)
library(rpart.plot)
library(rattle)
```

```
## Loading required package: tibble
```

```
## Loading required package: bitops
```

```
## Rattle: A free graphical interface for data science with R.
## Versión 5.5.1 Copyright (c) 2006-2021 Togaware Pty Ltd.
## Escriba 'rattle()' para agitar, sacudir y  rotar sus datos.
```

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(ggplot2)
library(RColorBrewer)
library(caret)
```

```
## Loading required package: lattice
```

```
library(ggfortify)
library(readr)
library(factoextra)
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WBa
```

```
require(corrplot)
```

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

```
## corrplot 0.92 loaded
```

```
set.seed(1)
```

Lectura del dataset

```
precios_madrid <- read.csv("PreciosMadrid.csv")
head(precios_madrid)
```

```
##     web_id                                                 url
## 1 99439319 https://www.idealista.com/en/inmueble/99439319/
## 2 99439586 https://www.idealista.com/en/inmueble/99439586/
## 3 99439169 https://www.idealista.com/en/inmueble/99439169/
## 4 26925909 https://www.idealista.com/en/inmueble/26925909/
## 5 99440018 https://www.idealista.com/en/inmueble/99440018/
## 6 99440142 https://www.idealista.com/en/inmueble/99440142/
##                                              title      type price deposit
## 1         Flat / apartment for rent in pablo luna, 4      Flat  1400      NA
## 2             Penthouse for rent in calle de Bolivia Penthouse  1300       1
## 3          Duplex for rent in calle de la constancia    Duplex   950       1
## 4 Flat / apartment for rent in Urb. el viso, El Viso      Flat  2975       1
## 5               Studio flat for rent in luis cabrera    Studio   650       1
## 6   Flat / apartment for rent in calle de Nieremberg      Flat  1200      NA
##   private_owner    professional_name floor_built floor_area floor year_built
## 1         False Silcasas Ochocientas          60         NA   3rd       1954
## 2         False              Cruzity          77         NA   6th       1961
## 3         False              Mm Home          72         68   3rd       1999
## 4         False         B&H Partners         160         NA   3rd         NA
## 5         False  Madrid en Propiedad          30         NA   4th         NA
## 6         False   Extra Inmobiliaria          54         47   4th       2009
##   orientation bedrooms bathrooms second_hand lift garage_included furnished
## 1                   2         1        True True           False      True
## 2                   2         2        True True           False      True
## 3        east       1         1        True True           False      True
## 4        west       4         3        True True            True      True
## 5                   0         1        True True           False      True
## 6        west       1         1        True True           False      True
##   equipped_kitchen fitted_wardrobes air_conditioning terrace balcony storeroom
## 1             True             True             True    True   False     False
## 2             True            False            False   False   False     False
## 3             True             True             True    True   False     False
```

```
## 4            True            True            True    True   False     False
## 5            True            True           False   False    True     False
## 6            True            True            True   False   False      True
##   swimming_pool garden_area
## 1         False       False
## 2         False       False
## 3         False       False
## 4          True       False
## 5         False       False
## 6          True       False
##                                                                                                l
## 1                        pablo luna, 4, Subdistrict Castilla, District Chamartín, Madrid, Madrid city,
## 2    Calle de Bolivia, Subdistrict Bernabéu-Hispanoamérica, District Chamartín, Madrid, Madrid city,
## 3 Calle de la constancia, Urb. no, Subdistrict Prosperidad, District Chamartín, Madrid, Madrid city,
## 4                          Urb. el viso, Subdistrict El Viso, District Chamartín, Madrid, Madrid city,
## 5                      luis cabrera, Subdistrict Prosperidad, District Chamartín, Madrid, Madrid city,
## 6           Calle de Nieremberg, Subdistrict Ciudad Jardín, District Chamartín, Madrid, Madrid city,
##    district             subdistrict postalcode last_update
## 1 Chamartín                Castilla      28046  7 November
## 2 Chamartín Bernabéu-Hispanoamérica      28016  7 November
## 3 Chamartín             Prosperidad      28002  7 November
## 4 Chamartín                 El Viso         NA  7 November
## 5 Chamartín             Prosperidad      28002  7 November
## 6 Chamartín           Ciudad Jardín      28002  7 November
```

```
colnames(precios_madrid)
```

```
##  [1] "web_id"            "url"               "title"
##  [4] "type"              "price"             "deposit"
##  [7] "private_owner"     "professional_name" "floor_built"
## [10] "floor_area"        "floor"             "year_built"
## [13] "orientation"       "bedrooms"          "bathrooms"
## [16] "second_hand"       "lift"              "garage_included"
## [19] "furnished"         "equipped_kitchen"  "fitted_wardrobes"
## [22] "air_conditioning"  "terrace"           "balcony"
## [25] "storeroom"         "swimming_pool"     "garden_area"
## [28] "location"          "district"          "subdistrict"
## [31] "postalcode"        "last_update"
```

Despues de analizar el dataset elijo las columnas que parecen mas interesantes

```
predata1 <- select(precios_madrid,price,floor_built,bathrooms,terrace,bedrooms,postalcode,garage_include
head(predata1)
```

```
##   price floor_built bathrooms terrace bedrooms postalcode garage_included
## 1  1400          60         1    True        2      28046           False
## 2  1300          77         2   False        2      28016           False
## 3   950          72         1    True        1      28002           False
## 4  2975         160         3    True        4         NA            True
## 5   650          30         1   False        0      28002           False
## 6  1200          54         1   False        1      28002           False
```

```
colnames(predata1)
```

```
## [1] "price"           "floor_built"     "bathrooms"       "terrace"
## [5] "bedrooms"        "postalcode"      "garage_included"
```

Elimino pisos que cuesten 0, tengan 0 habitaciones,esten repetidos o sean NA. Tambien para acotar el dataset vamos a coger solo los anuncios de 10 postalcode

```
predata2 = subset(predata1, price>0 & bedrooms>1 & postalcode>=28001 & postalcode<=28011)
predata2 <- na.omit(predata2)
predata <- unique(predata2)
```

Convertir las columnas de valores char("True","False") en num(1,0).Tambien estandarizo todo en numeric

```
predata$terrace <- as.numeric(as.logical(predata$terrace))
predata$garage_included <- as.numeric(as.logical(predata$garage_included))
predata$postalcode <- as.numeric(as.integer(predata$postalcode))
predata$price <- as.numeric(as.integer(predata$price))
predata$floor_built <- as.numeric(as.integer(predata$floor_built))
predata$bathrooms <- as.numeric(as.integer(predata$bathrooms))
predata$bedrooms <- as.numeric(as.integer(predata$bedrooms))
```

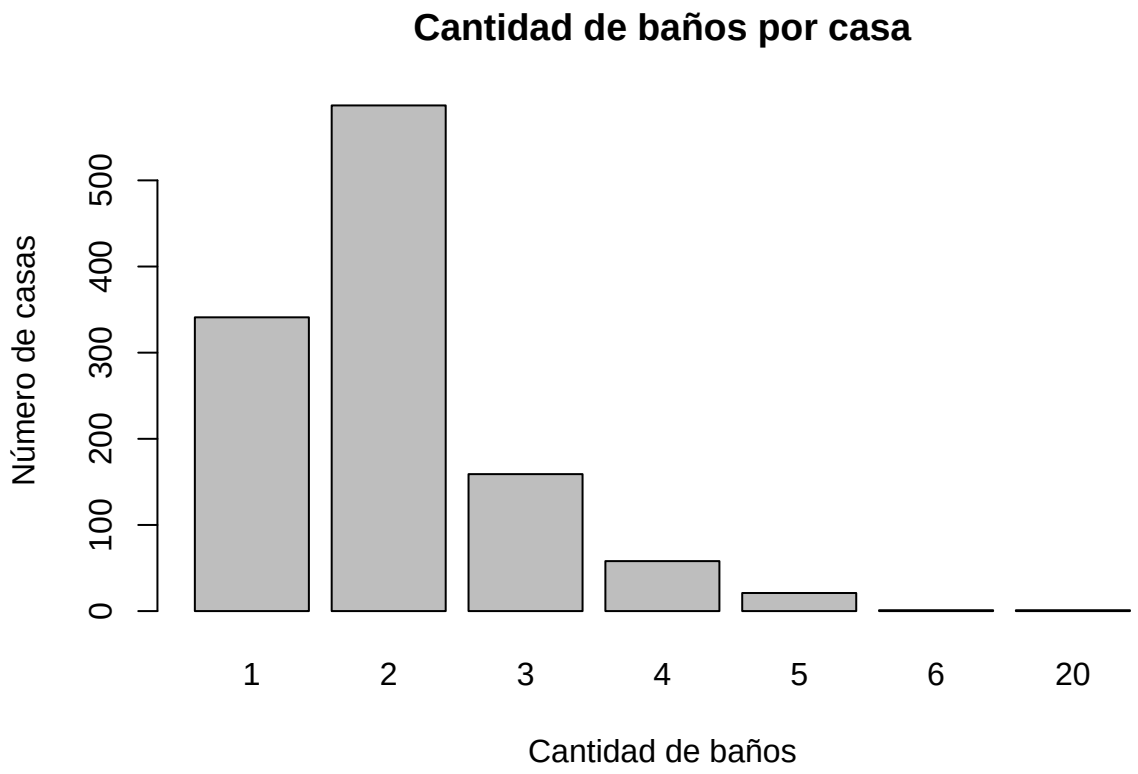
Finalmente despues del preprocesamiento de datos, obtenemos el dataset final

```
data<-predata
```

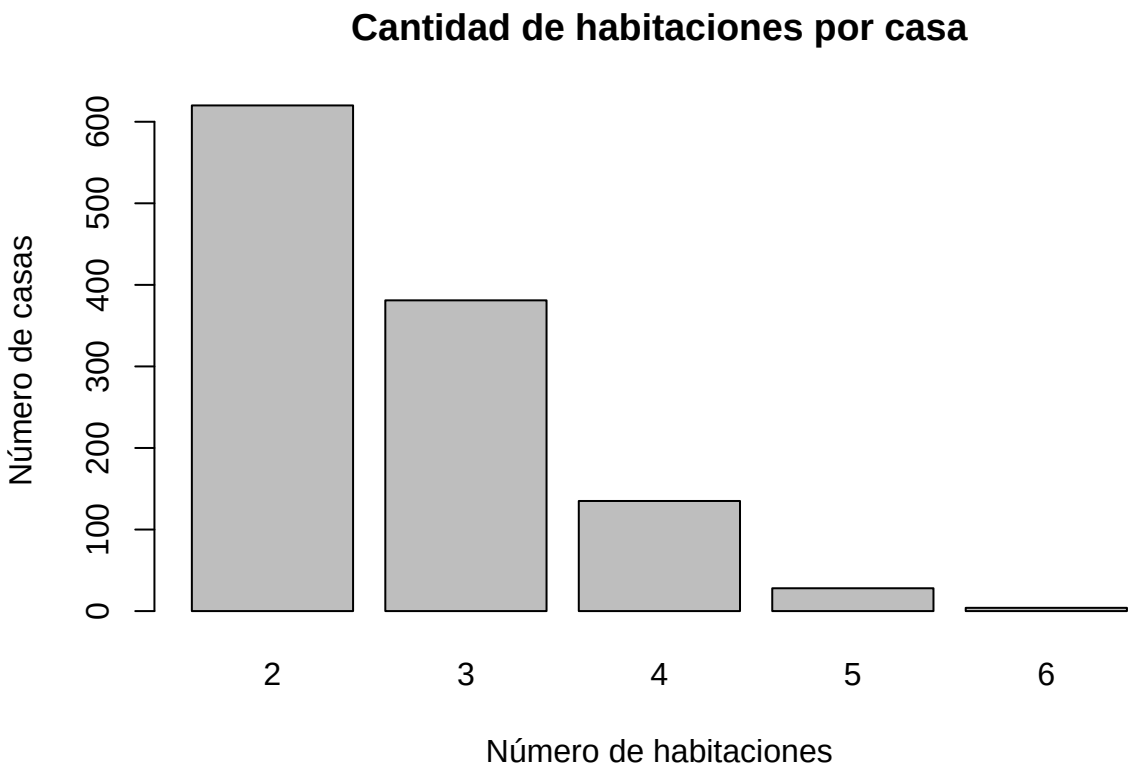
Una vez con los datos bien definido, pasamos a la visualización.

```
barplot(table(data$terrace),
main="Número de casas con terraza",
xlab="Tiene o no terraza",
ylab="Número de casas",)
```


```
barplot(table(data$bathrooms),
main="Cantidad de baños por casa",
xlab="Cantidad de baños",
ylab="Número de casas",)
```

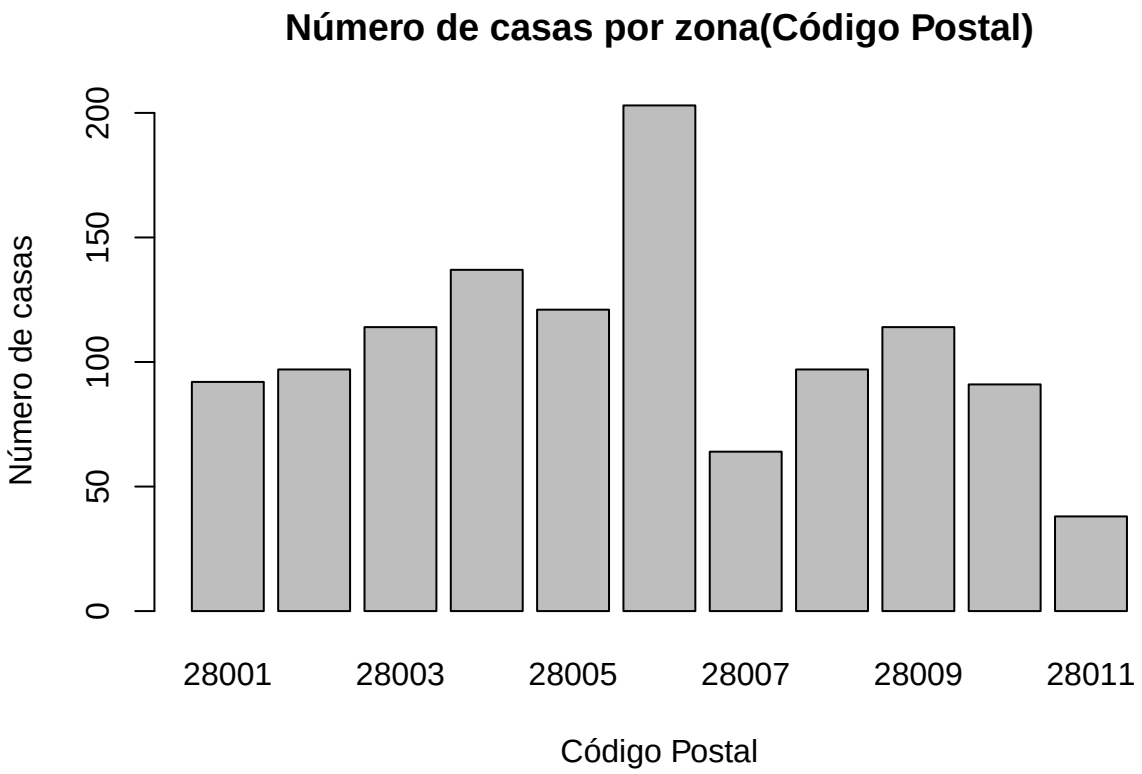



```
barplot(table(data$bedrooms),
main="Cantidad de habitaciones por casa",
xlab="Número de habitaciones",
ylab="Número de casas",)
```



Primero vamos a ver el número de casas por código postal.

```
barplot(table(data$postalcode),
main="Número de casas por zona(Código Postal)",
xlab="Código Postal",
ylab="Número de casas",)
```

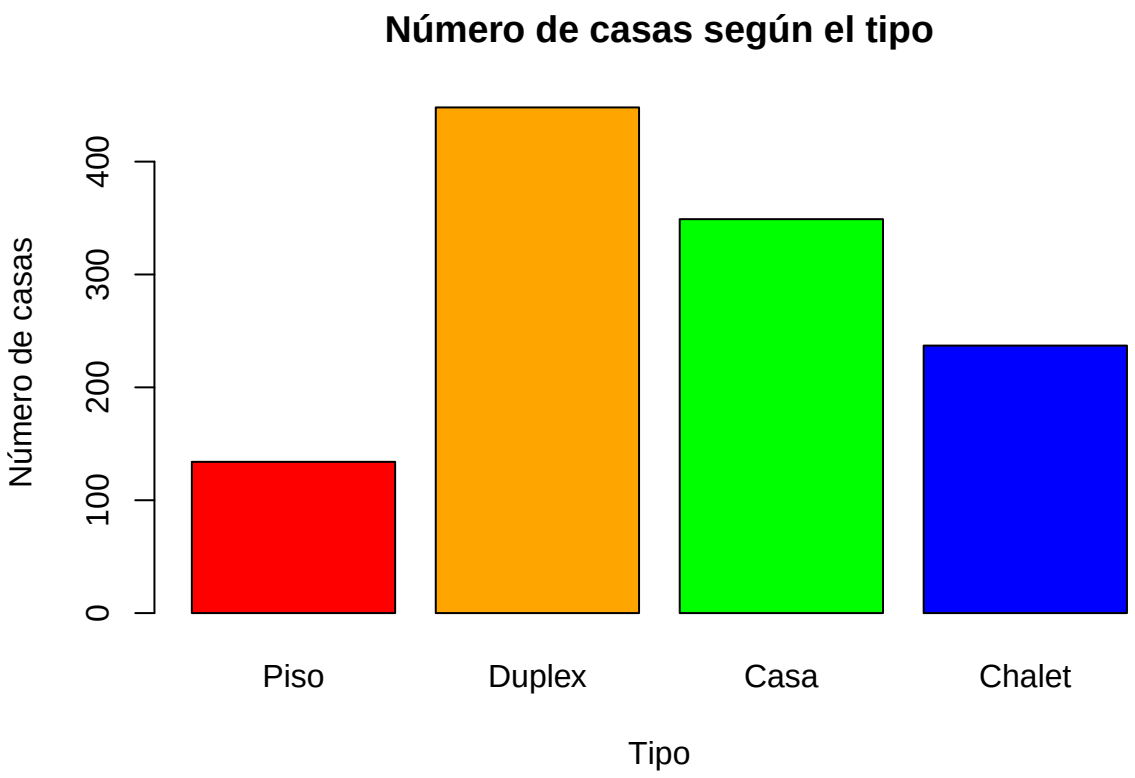


Vamos a etiquetar y categorizar según los metros construidos, con el objetivo de ver los tipos de viviendas

```
data_metros <- data

head(data_metros[order(data_metros$floor_built),])
```

```
##      price floor_built bathrooms terrace bedrooms postalcode garage_included
## 7018  1750          30         1       0        2      28009               0
## 2497   800          35         1       0        2      28005               0
## 1376  1990          40         1       0        2      28009               0
## 1537   850          40         1       0        2      28009               0
## 1550   750          40         1       0        2      28009               0
## 1627   950          40         1       0        2      28010               0
```

```
rangos <- c(0,65,100,150,Inf)
values <- c ('Piso','Duplex','Casa','Chalet')

data_metros$tipo <- cut(data_metros$floor_built, breaks = rangos, labels = values)

barplot(table(data_metros$tipo),
main="Número de casas según el tipo",
xlab="Tipo",
ylab="Número de casas",
col=c("red","orange","green","blue"),)
```



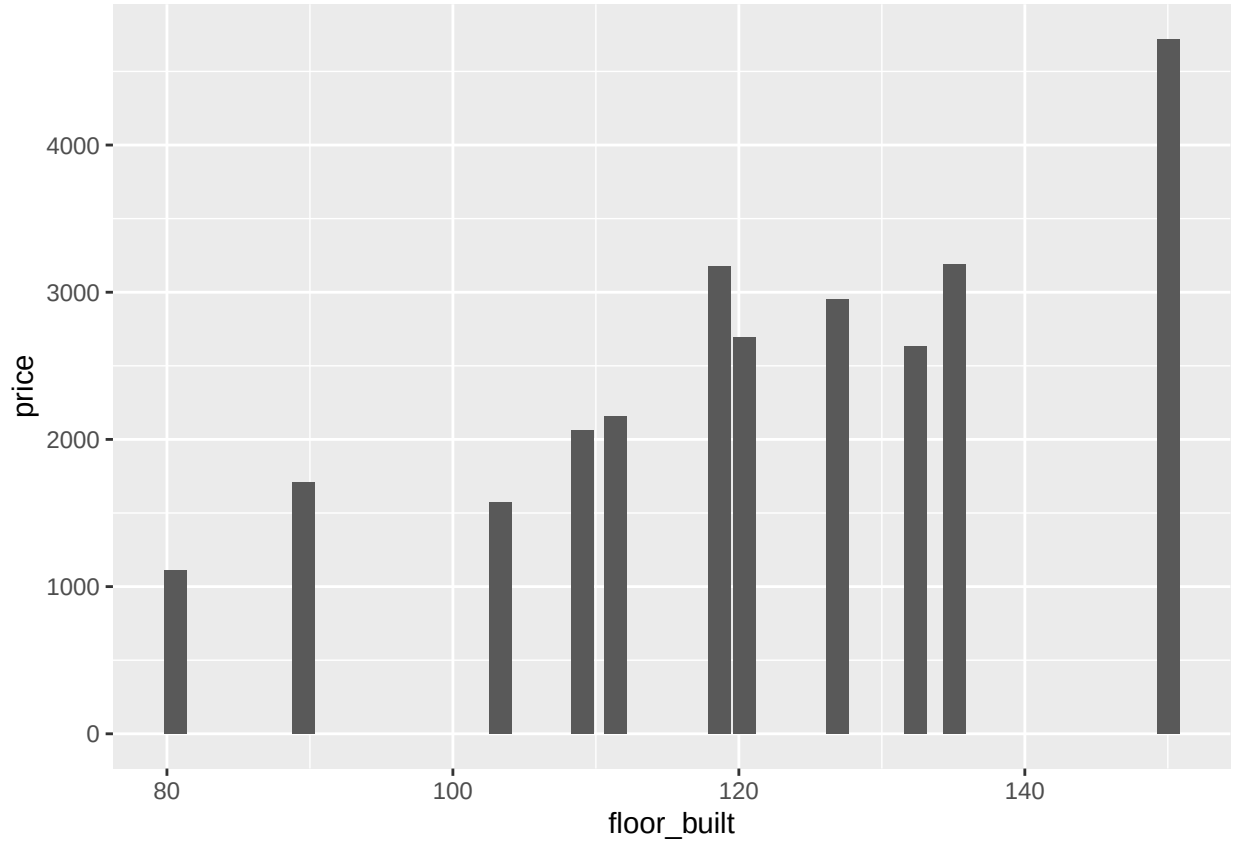
Vamos a calcular el precio medio, metros construidos y los tipos de casas dependiendo de la zona (Código postal). Para el tipo de casa pasamos a numeric con la asignación por defecto el 1 a pisos, 2 a duplex... De esta manera obtendremos una media del tipo de casa por zona

```
data_metros$tipo <- as.numeric(as.factor(data_metros$tipo))
media1 <- aggregate(data_metros[, c(1,2,8)], list(data_metros$postalcode), mean)
media1
```

```
##    Group.1    price floor_built     tipo
## 1    28001 4720.315   150.02174 3.000000
## 2    28002 2155.979   111.34021 2.402062
## 3    28003 2632.711   132.33333 2.859649
## 4    28004 3177.555   118.61314 2.671533
## 5    28005 1710.264    89.57025 2.066116
## 6    28006 3186.567   135.08867 2.807882
## 7    28007 1570.141   103.35938 2.468750
## 8    28008 2063.856   109.04124 2.402062
## 9    28009 2694.211   120.39474 2.657895
## 10   28010 2953.846   126.87912 2.637363
## 11   28011 1108.816    80.57895 1.842105
```

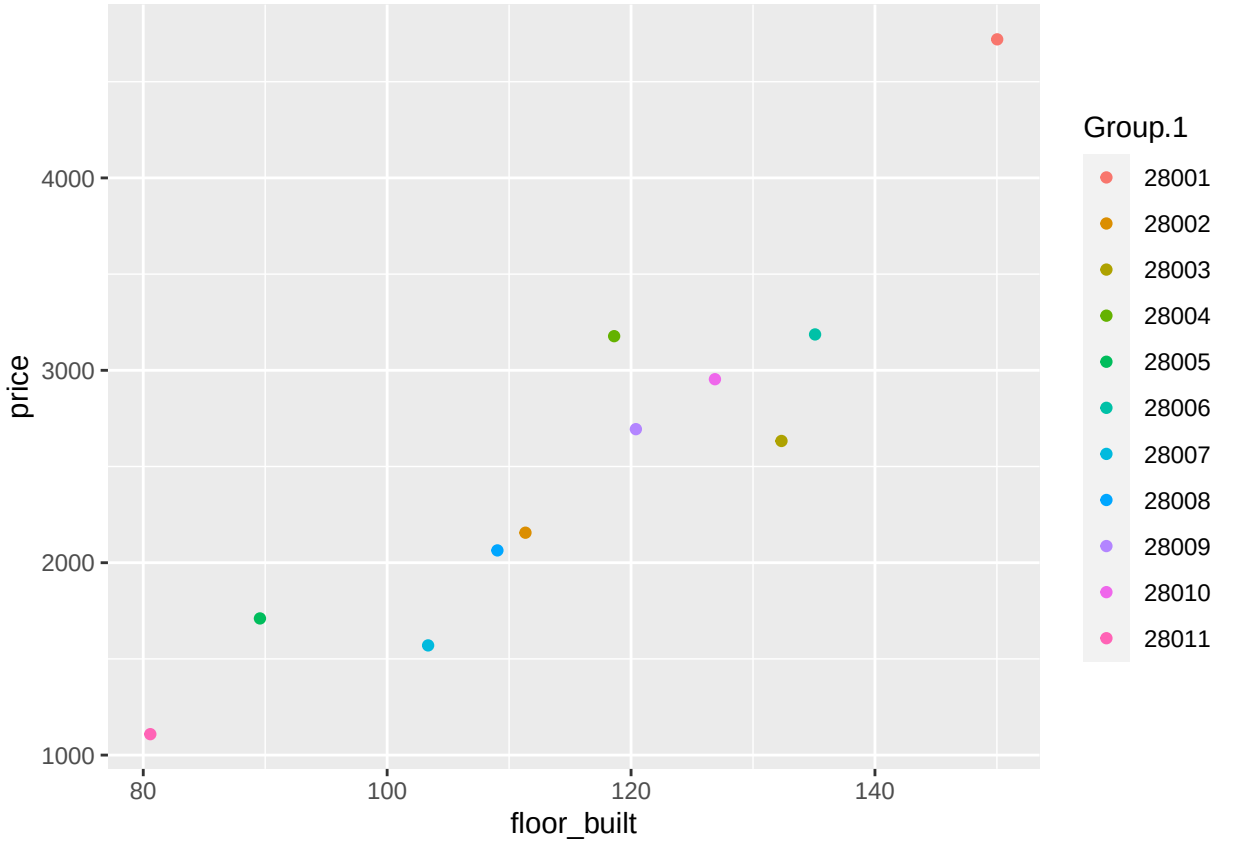
Vamos a graficar la media de precio según los metros construidos de media en barras, para ver si vemos algo interesante

```
ggplot(media1, aes(x = floor_built, y = price)) +
        geom_col()
```



Nos percatamos de que en algunos casos en los que no se cumple que a mayor metros mayor precio.Vamos a graficar la media de precio según los metros construidos de media por zonas en puntos

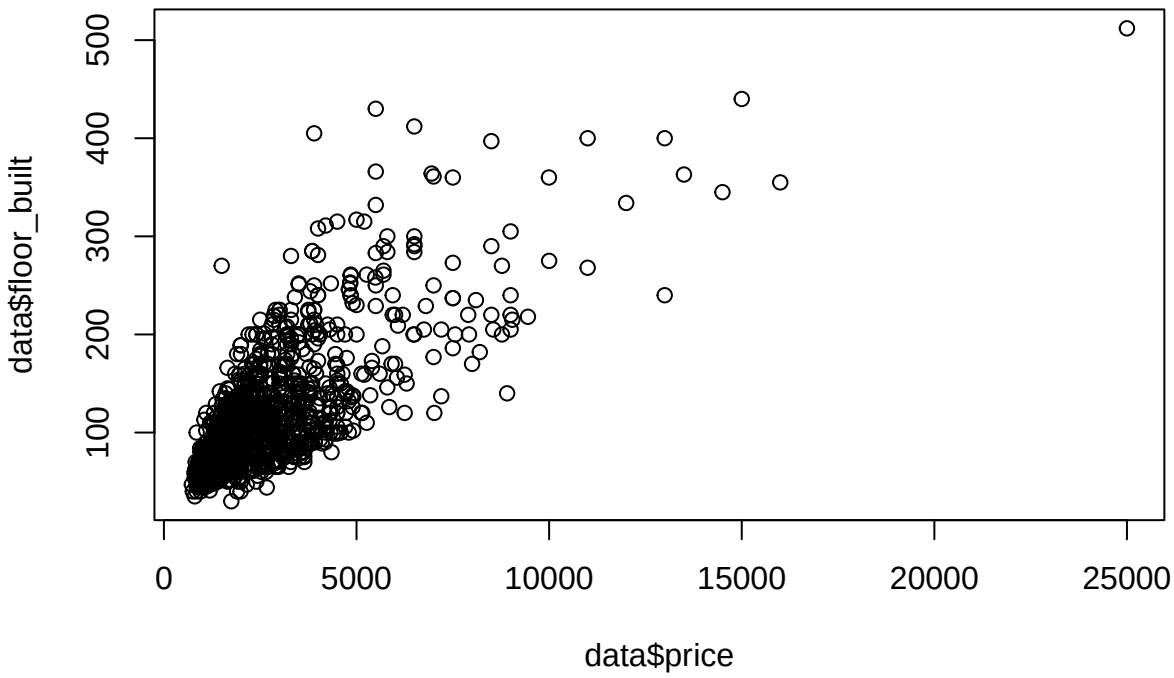
```
#Pasamos a factor el codigo postal para ver mejor el codigo de colores
media1$Group.1 <- as.factor(as.numeric(media1$Group.1))
ggplot(media1, aes(x= floor_built, y=price, colour=Group.1)) + geom_point()
```



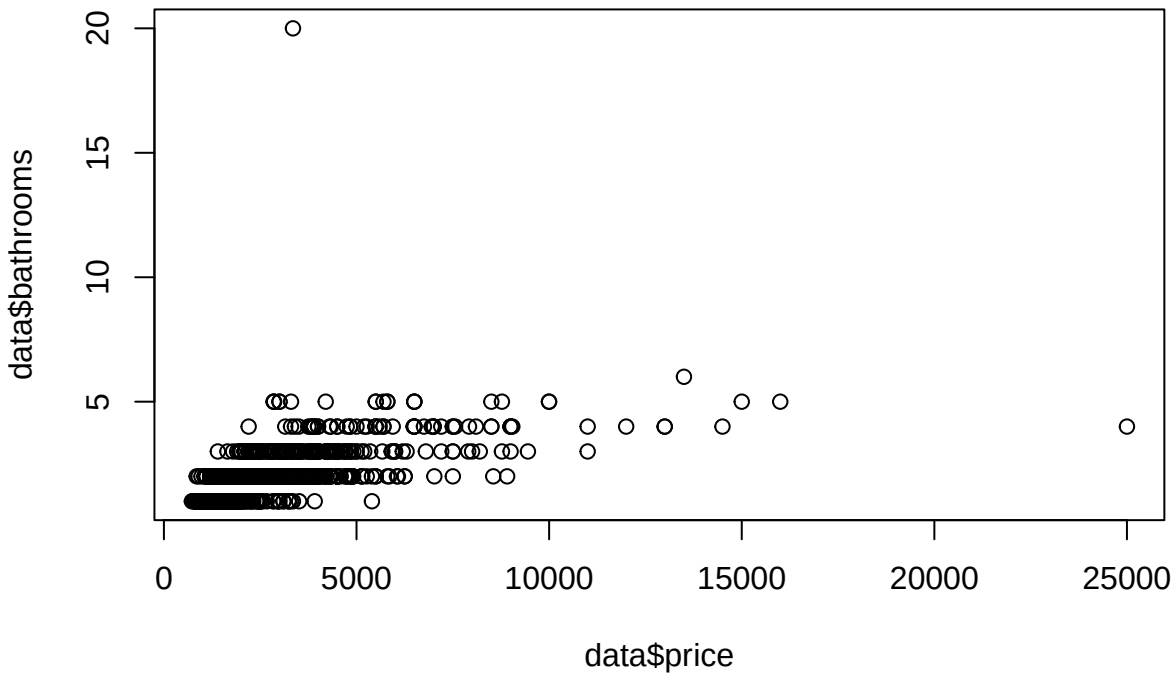
También vamos a hacer algunos analisis para ver como influyen otras variables, como el garaje, terraza...

Gráficas de dispersión, para observar la relación entre las variables.

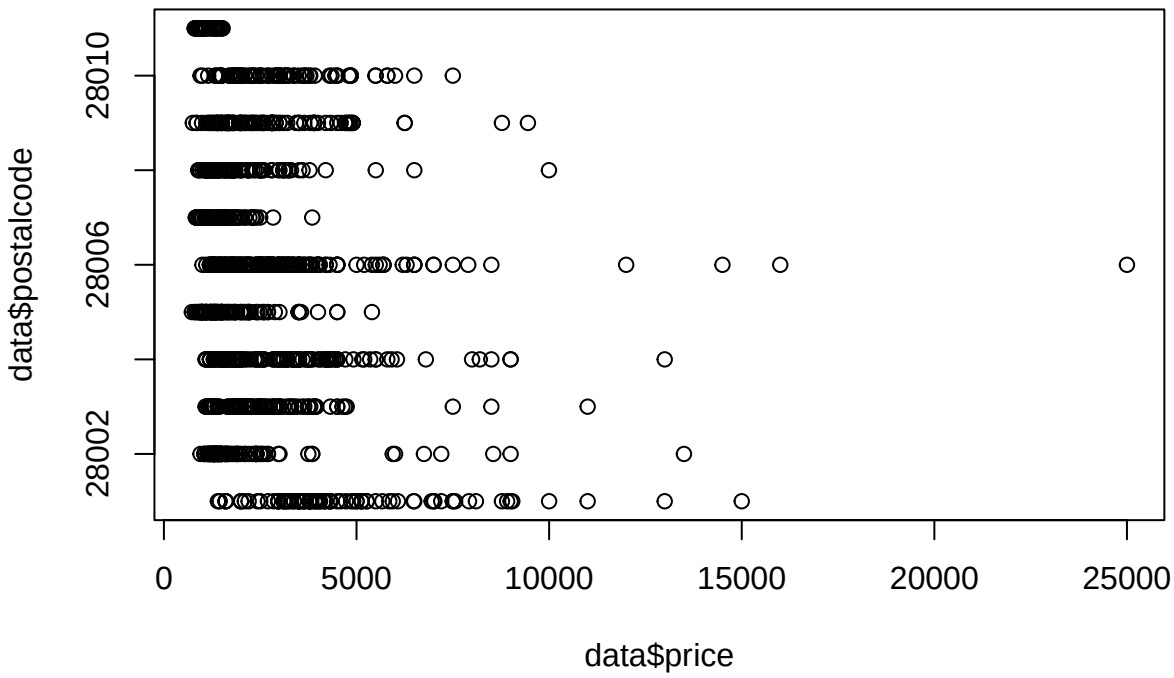
```
plot(x = data$price, y = data$floor_built)
```



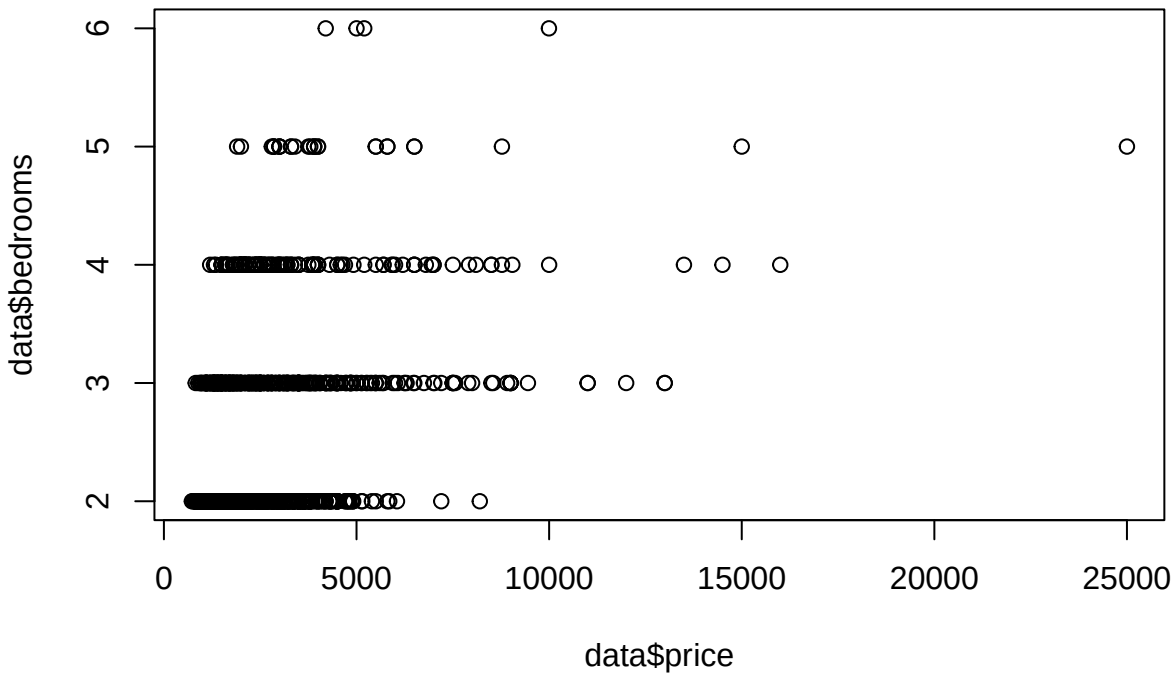

```
plot(x = data$price, y = data$bathrooms)
```




```
plot(x = data$price, y = data$postalcode)
```



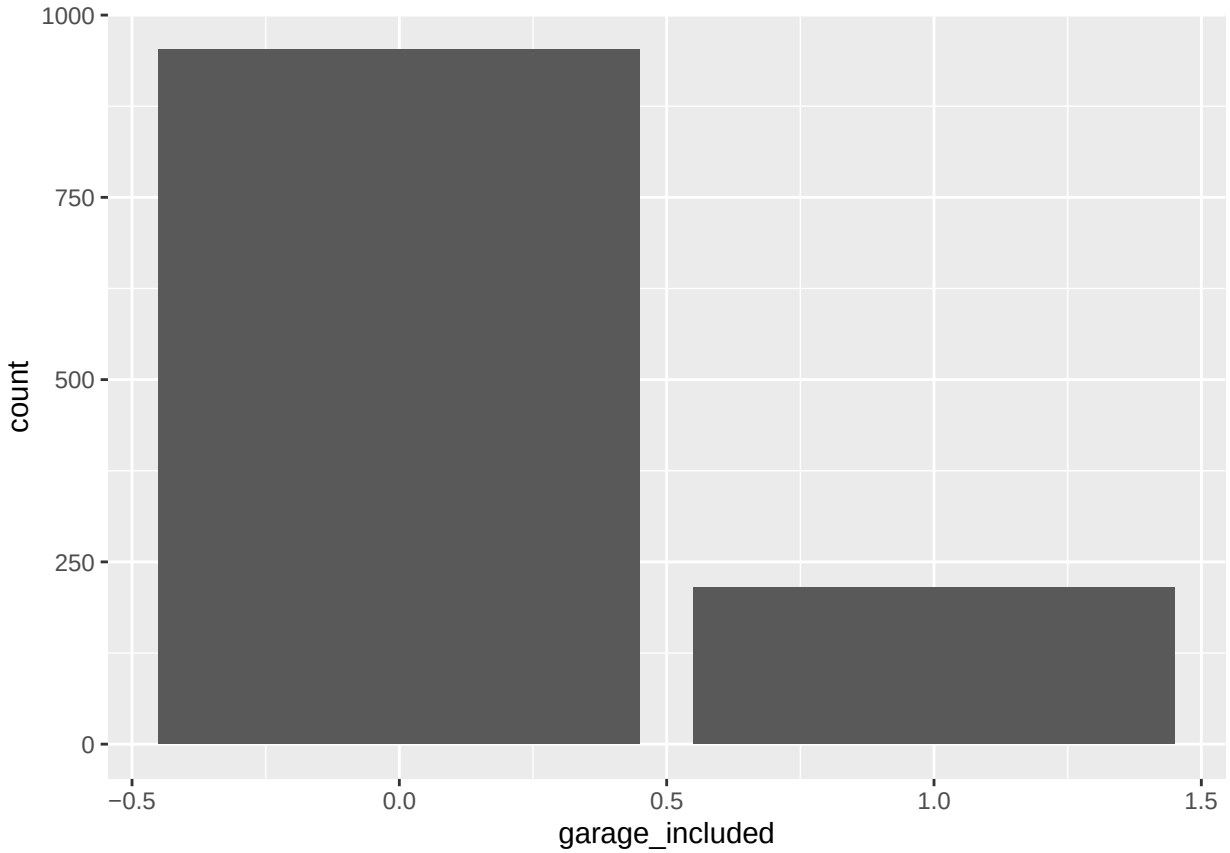

```
plot(x = data$price, y = data$bedrooms)
```



Gráfica para saber dependiendo del tipo de casa si lleva garage o no. Podriamos hacer esto con las diferentes variables, solo habría que cambiar el valor del aes.

```
a<- ggplot(data_metros, aes(garage_included))
a + geom_bar(aes(fill = tipo))
```

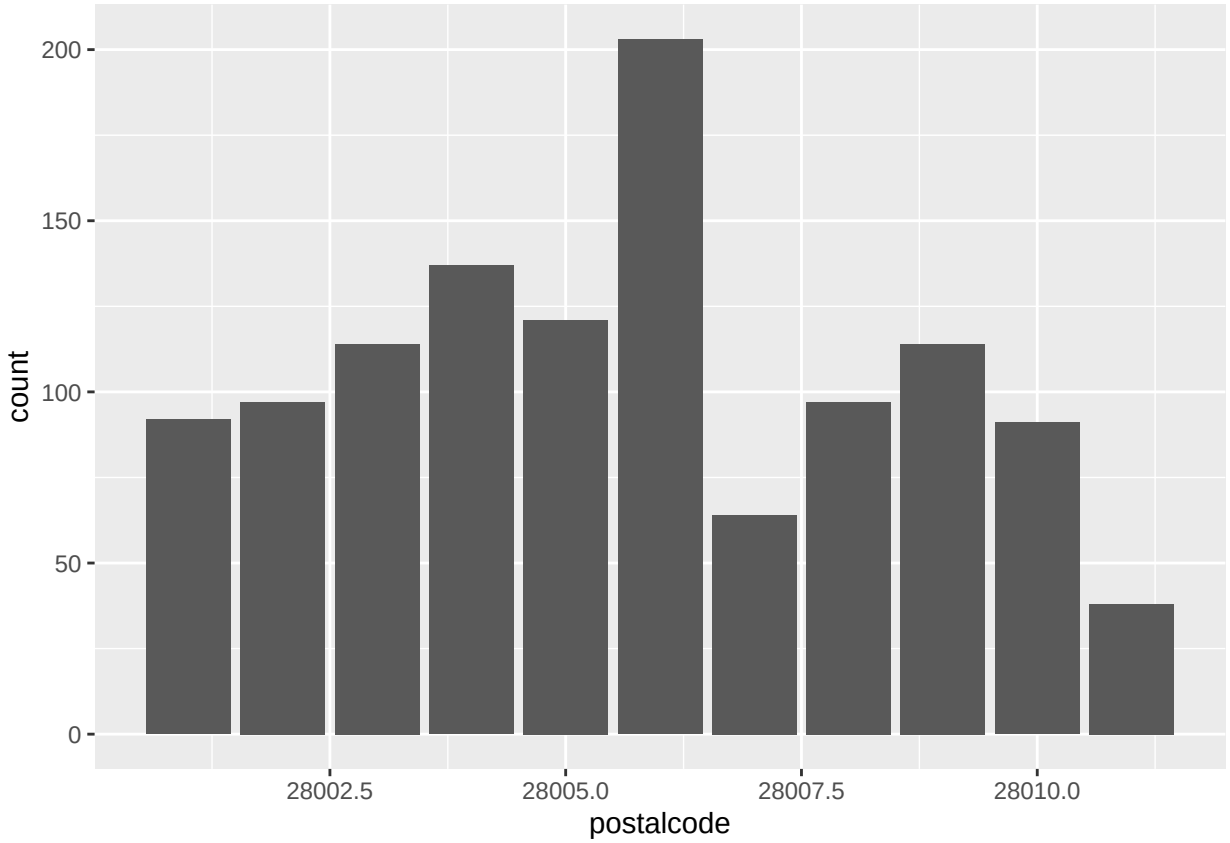
```
## Warning: The following aesthetics were dropped during statistical transformation: fill
## i This can happen when ggplot fails to infer the correct grouping structure in
##   the data.
## i Did you forget to specify a ‘group‘ aesthetic or to convert a numerical
##   variable into a factor?
```



Gráfica según el número de tipos de casas por zona

```
a<- ggplot(data_metros, aes(postalcode))

a + geom_bar(aes(fill = tipo))
```

```
## Warning: The following aesthetics were dropped during statistical transformation: fill
## i This can happen when ggplot fails to infer the correct grouping structure in
##   the data.
## i Did you forget to specify a ‘group‘ aesthetic or to convert a numerical
##   variable into a factor?
```



Analasis supervisado:

Después de haber estado jugando con las variables, vamos a aplicar diferentes tecnicas. Primero categirizamos los precios del dataset

```
data_analisis<-data
nrow(data_analisis)
```

```
## [1] 1168
```

```
rangos <- c(0,1300,2500,Inf)
values <- c ('barata','normal','cara')

data_analisis$categoria <- cut(data_analisis$price, breaks = rangos, labels = values)
```

```
data_analisis <- data_analisis %>%
select(-c(price))
```

```
data_agrupada <- data_analisis %>%
group_by( floor_built, bathrooms, bedrooms, garage_included, terrace,postalcode,categoria) %>%
count() %>%
arrange(desc(n()))
```

```
data_agrupada <- data_agrupada  %>%
rename(TotalCasas = n)
head(data_agrupada)
```

```
## # A tibble: 6 x 8
## # Groups:   floor_built, bathrooms, bedrooms, garage_included, terrace,
## #   postalcode, categoria [6]
##   floor_built bathrooms bedrooms garage_included terrace posta~1 categ~2 Total~3
##         <dbl>     <dbl>    <dbl>           <dbl>   <dbl>   <dbl> <fct>     <int>
## 1          30         1        2               0       0   28009 normal        1
## 2          35         1        2               0       0   28005 barata        1
## 3          40         1        2               0       0   28005 normal        1
## 4          40         1        2               0       0   28009 barata        2
## 5          40         1        2               0       0   28009 normal        1
## 6          40         1        2               0       0   28010 barata        1
## # ... with abbreviated variable names 1: postalcode, 2: categoria,
## #   3: TotalCasas
```

Primero partimos el dataset para tener datos de entrenamiento y datos de validacion.

```
train <-createDataPartition(data_agrupada$categoria, p = 0.7, list=FALSE)
validos <-createDataPartition(data_agrupada$categoria, p = 0.7, list=FALSE)
data_train <- data_agrupada[train,]
data_val <- data_agrupada[validos,]
nrow(data_train)
```

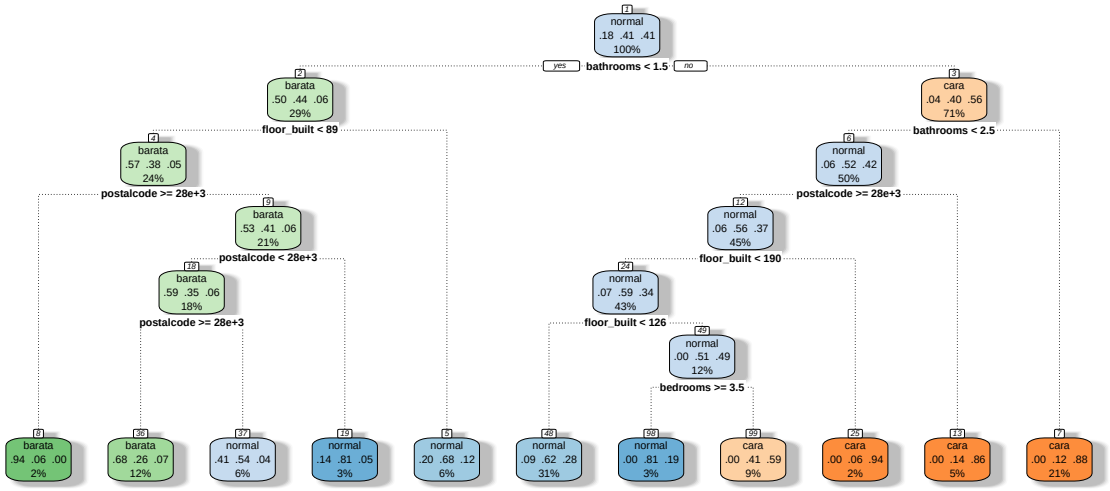
```
## [1] 737
```

```
nrow(data_val)
```

```
## [1] 737
```

Realizando el arbol podemos ver las diferentes variables que afectan a su precio y en que nos podemos basar para aproximar el precio medio de una vivienda.

```
arbol <- rpart(formula =  categoria  ~ ., data = data_train, method = 'class')

fancyRpartPlot(arbol)
```



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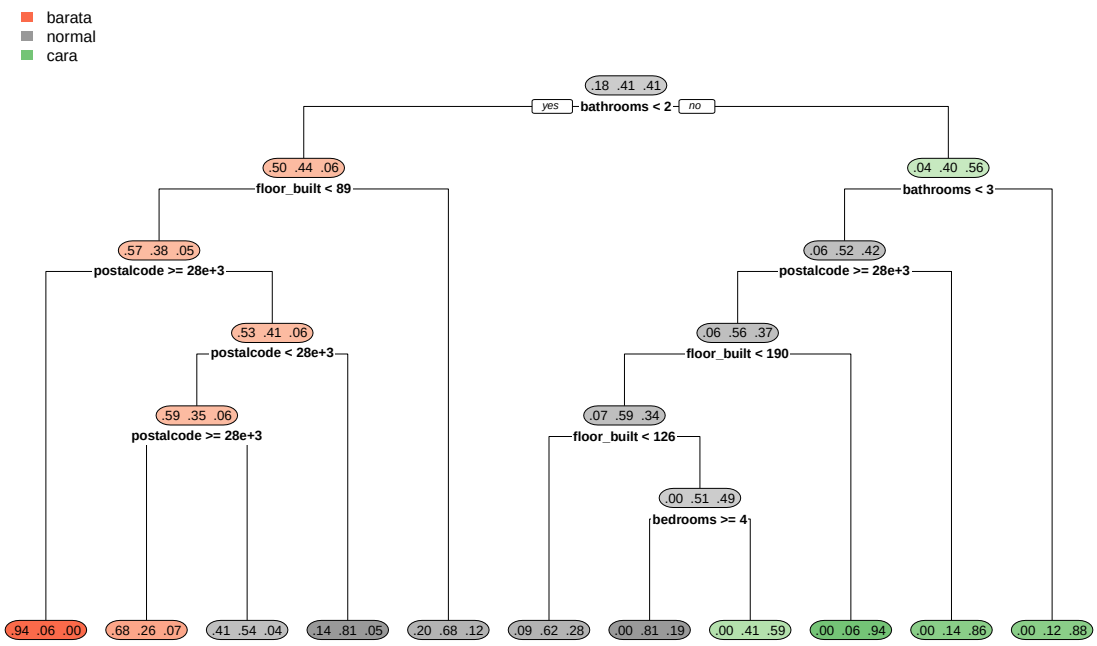
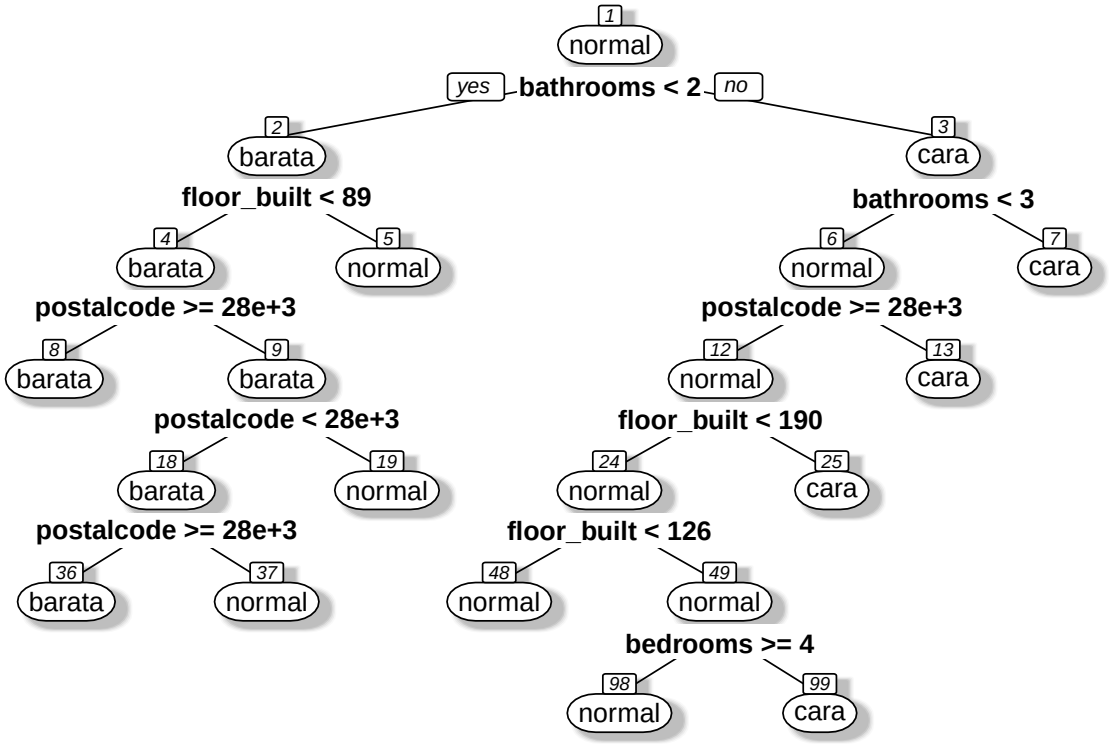
Hacemos un par de cambios en la visualizacion para verlo mejor.

```
rpart.plot(arbol, extra = 5)
```




```
prp(arbol, type = 2, nn = TRUE,
    fallen.leaves = FALSE,
    varlen = 0,  shadow.col = "gray")
```



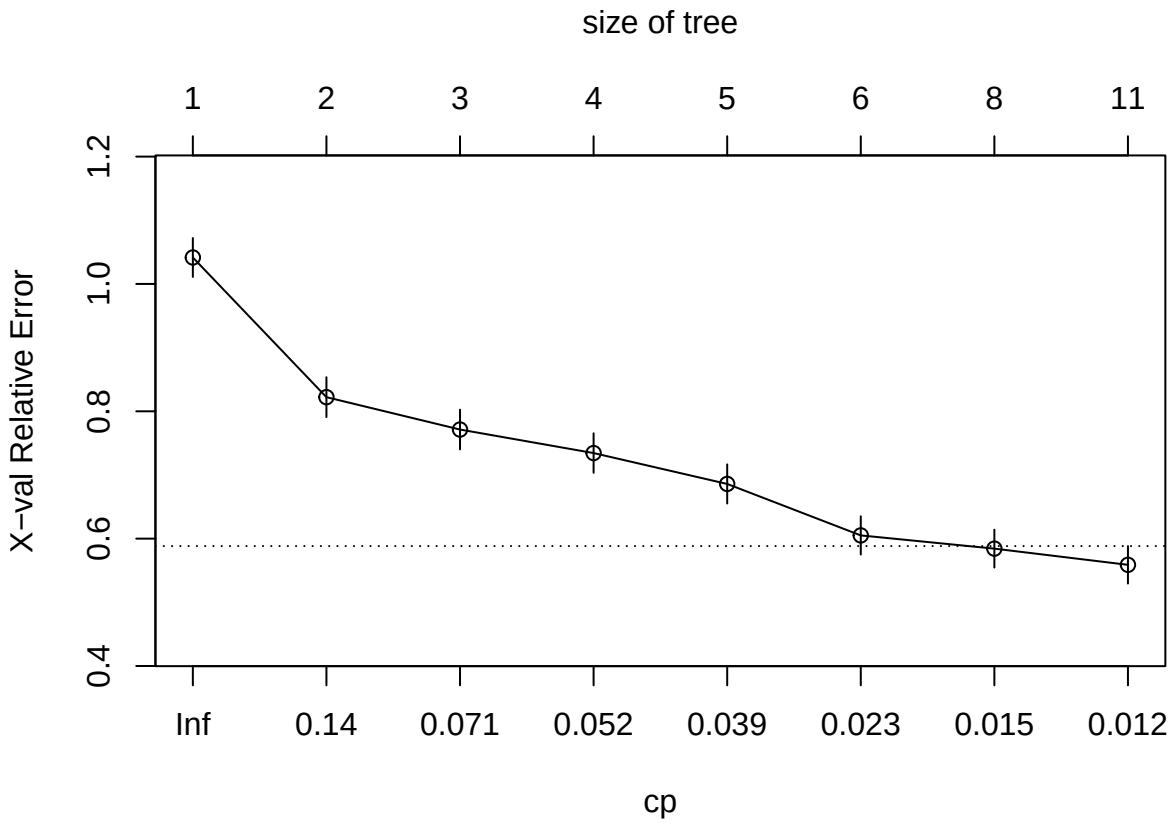
Observamos que los metros construidos y los cuartos de baños son las variables que mas afectan.

Vamos a ver el cp

```
arbol$cptable
```

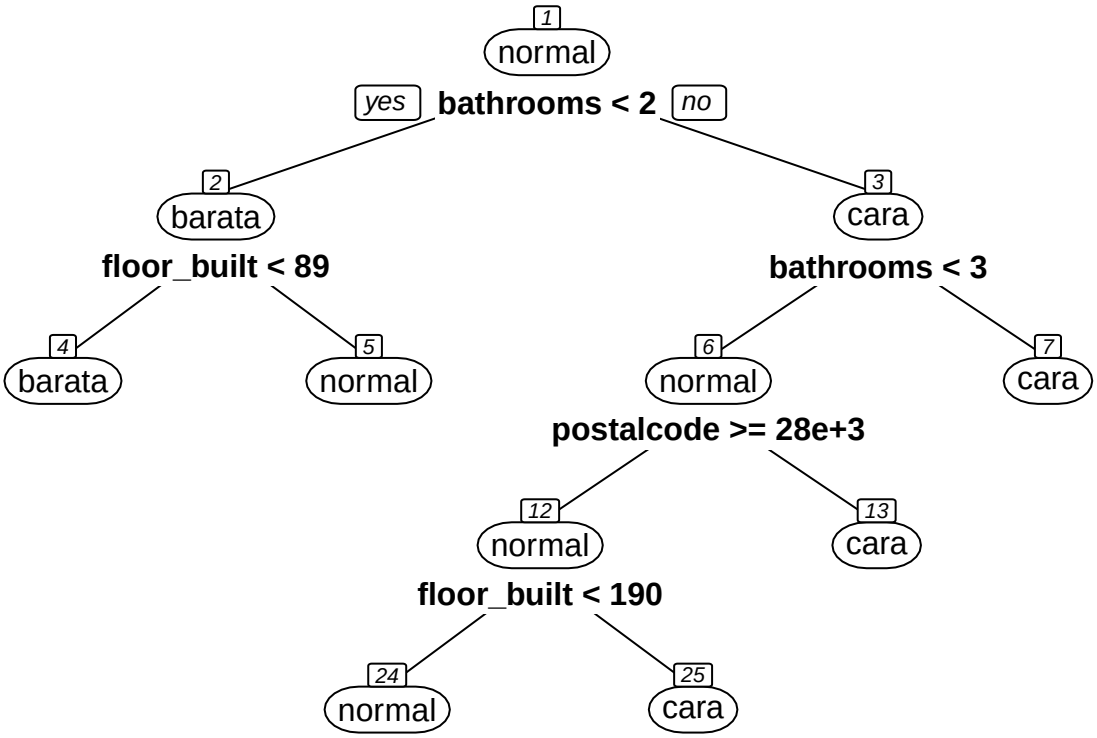
```
##           CP nsplit rel error    xerror       xstd
## 1 0.21709007      0 1.0000000 1.0415704 0.03055270
## 2 0.08775982      1 0.7829099 0.8221709 0.03133039
## 3 0.05773672      2 0.6951501 0.7713626 0.03121074
## 4 0.04618938      3 0.6374134 0.7344111 0.03105267
## 5 0.03233256      4 0.5912240 0.6859122 0.03075268
## 6 0.01616628      5 0.5588915 0.6050808 0.03001068
## 7 0.01385681      7 0.5265589 0.5842956 0.02976880
## 8 0.01000000     10 0.4849885 0.5588915 0.02944345
```

```
plotcp(arbol)
```



Podamos el arból para reducirlo, usando el cp obtenido anteriormente

```
arbol_podado <- prune(arbol, cp = 0.017)
prp(arbol_podado, type = 2, nn = TRUE,
    fallen.leaves = FALSE,
    varlen = 0)
```



Predecimos en el data de validacion y sacamos la matrix de confusion

```
categoria_pred <- predict(arbol, newdata = data_val, type="class")

confunsion_m <- table(data_val$categoria, categoria_pred)
confunsion_m
```

```
##         categoria_pred
##          barata normal cara
##   barata     73     56    0
##   normal     21    231   52
##   cara        4     93  207
```

Calculamos el acierto

```
acierto <- sum(diag(confunsion_m)) / sum(confunsion_m)
acierto
```

```
## [1] 0.6933514
```

Vemos que solo tenemos un 67% de acierto, por lo que vamos a controlar el algoritmo de particion para ver si mejoramos

```
controlador <- rpart.control(minsplit = 10, minbucket = round(10 / 3), maxdepth = 4, cp = 0,015)
```

Luego volvemos a repetir todo el proceso

```
arbol2 <- rpart(categoria ~., data = data_train, method = 'class', control = controlador)

categoria_pred1 <- predict(arbol2, newdata = data_val, type="class")
confunsion_m1 <- table(data_val$categoria, categoria_pred1)
acierto2 <- sum(diag(confunsion_m1)) / sum(confunsion_m1)
acierto2
```

```
## [1] 0.6621438
```

Vemos que no mejoramos, por lo cual con la primera iteracion hemos sacado un % optimo.

Ahora pasamos a aplicar un metodo de regresion multiple para calcular el precio en funcion de las demas variables. Para esto si vamos a necesitar el precio y no la categoria

```
train_rg <-createDataPartition(data$price, p = 0.7, list=FALSE)
data_train_rg <- data[train_rg,]
data_val_rg <- data[-train_rg,]
nrow(data_train_rg)
```

```
## [1] 820
```

```
nrow(data_val_rg)
```

```
## [1] 348
```

```
regresion_mul <- lm(formula = price ~ ., data = data_train_rg)

summary(regresion_mul)
```

```
##
## Call:
## lm(formula = price ~ ., data = data_train_rg)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4839.6  -644.1  -176.8   485.5 12975.9
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      1.298e+06  4.231e+05   3.067  0.00223 **
## floor_built      2.647e+01  1.074e+00  24.646  < 2e-16 ***
## bathrooms        1.659e+02  5.135e+01   3.230  0.00129 **
## terrace         -2.560e+02  9.684e+01  -2.643  0.00837 **
## bedrooms        -5.159e+02  7.081e+01  -7.286 7.54e-13 ***
## postalcode      -4.632e+01  1.511e+01  -3.066  0.00224 **
## garage_included -2.742e+02  1.169e+02  -2.346  0.01921 *
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1204 on 813 degrees of freedom
## Multiple R-squared:  0.6096, Adjusted R-squared:  0.6067
## F-statistic: 211.6 on 6 and 813 DF,  p-value: < 2.2e-16
```

Segun el R^2 el modelo puede explicar en un 61% la variabilidad del precio, ya que R^2=0,6132 Tambien vemos que alguna variable predictor está relacionada con el precio ya que el p-value es bastante infimo.. No encontramos ninguna variable con un p-value alto por lo que nos indican que todas contribuyen en parte al modelo.

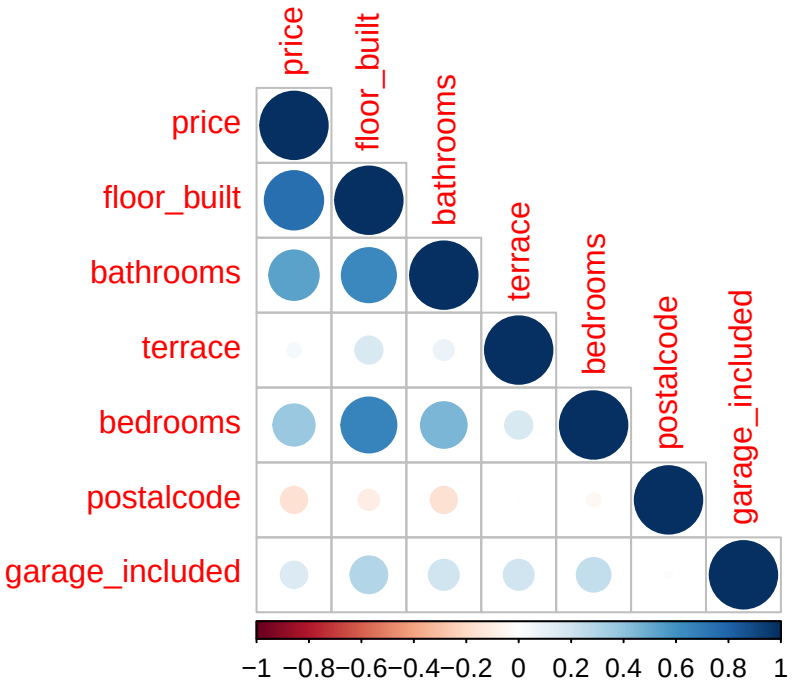
El metodo step, nos arroja que los metros construidos y los cuarto de baños son las variables que mas correlacion tienen. Los

```
step(regresion_mul, direction = "both", trace = 0)
```

```
##
## Call:
## lm(formula = price ~ floor_built + bathrooms + terrace + bedrooms +
##     postalcode + garage_included, data = data_train_rg)
##
## Coefficients:
##     (Intercept)      floor_built        bathrooms          terrace
##      1297834.55            26.47           165.88          -255.98
##        bedrooms       postalcode  garage_included
##         -515.94           -46.32          -274.16
```

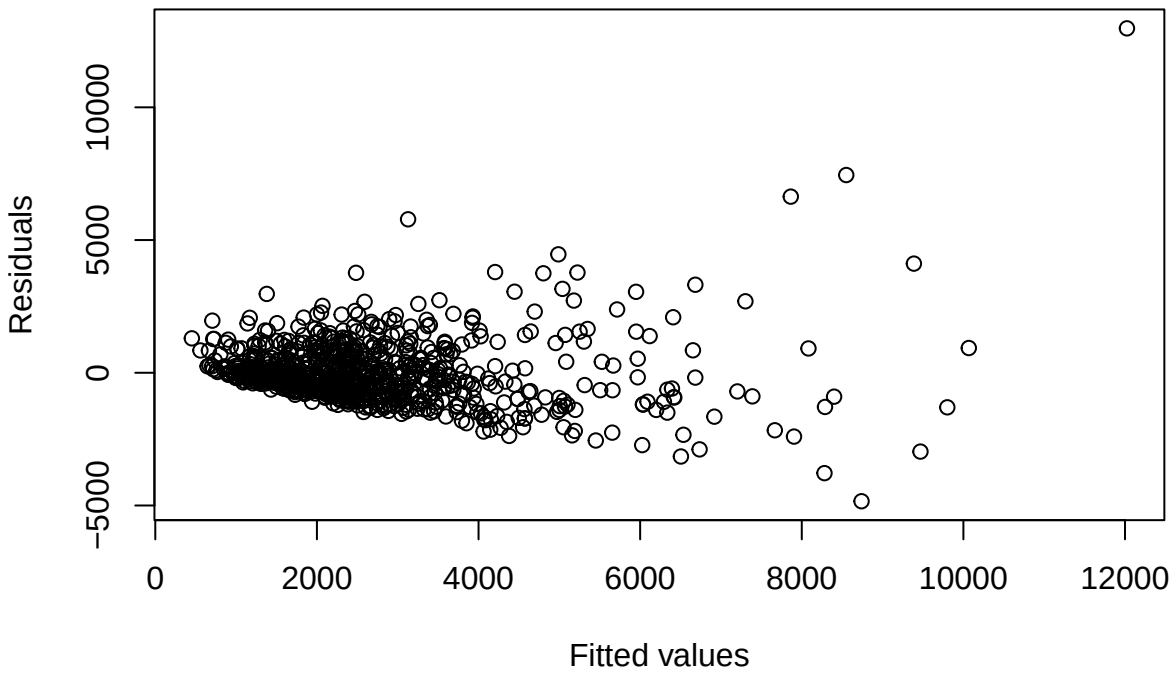
Hacemos un grafico corrplot para ver la correlacion con las variables, donde sacamos que las variables que mas influyen son los metros construidos, los cuarto de baños y las camas. Vemos según diferentes métodos que esas son las variables con mayor correlacion.

```
corrplot(cor(data_train_rg) ,type = "lower",)
```



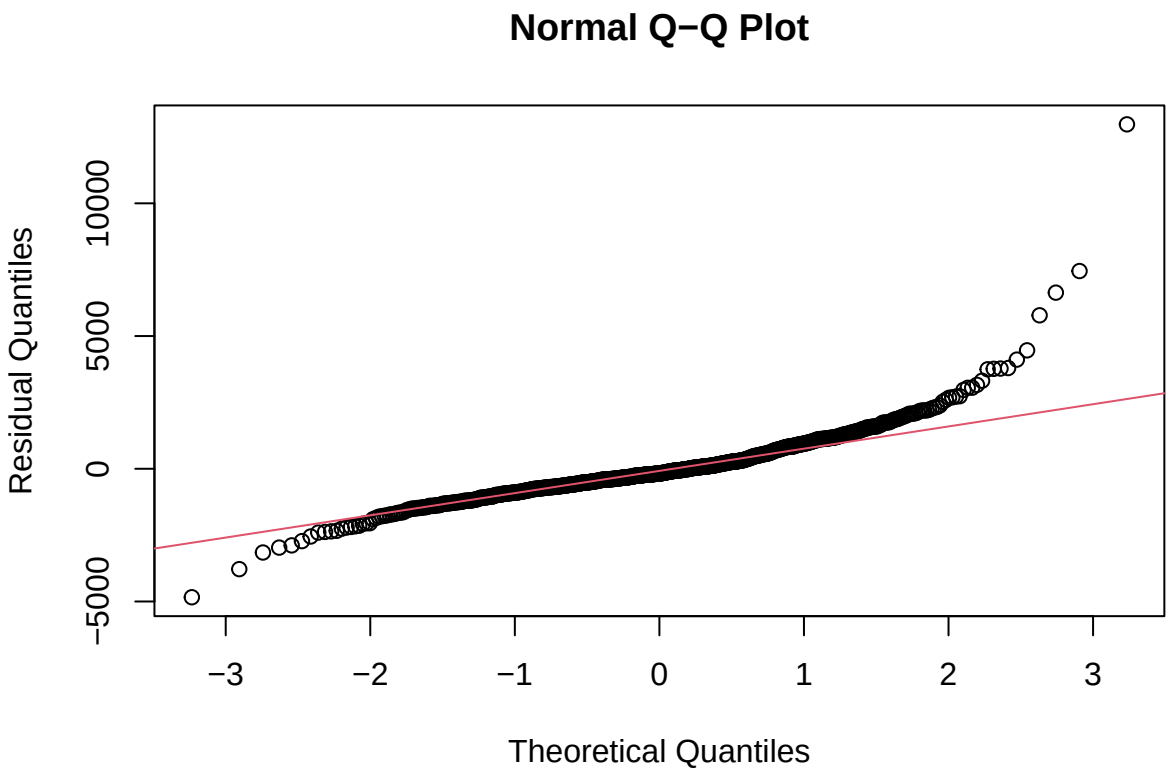
Ahora pasamos a graficar los residuos en funcion de los valores ajustados, es decir distancias entre los estimados y reales.

```
plot(regresion_mul$fitted.values,  regresion_mul$residuals,
     xlab = "Fitted values", ylab = "Residuals")
```



Sacamos el grafico Q-Q para comprar los residuos de dos distribuciones de probabilidad cuando trazamos los cuantiles entre ellos. No apreciamos ningun patron y podemos intuir que esta formanod una linea por lo que concluimos con que el modelo es bueno.

```
qqnorm(regresion_mul$residuals, ylab = "Residual Quantiles")
qqline(regresion_mul$residuals, col = 2)
```



Y vamos a predecir según la regresion multiple, luego compararemos con el arbol de decision.

```
data_val_regresion <-predict(regresion_mul, data_val_rg)
data_val_regresion
```

```
##          7         15         16         17         24         28         50
##  1182.1640  1186.8785  1186.8785  1570.4776  1332.6273  2176.8177  2001.0302
##         60         66         73         95         98        129        189
##  2318.6390  1478.0198  2364.4993  2160.1908  3129.6451  2637.8706  1914.5549
##        222        224        246        288        330        373        377
##  1723.3020  5389.9496  1894.3737  5389.9496  2040.9094  1354.3814  1235.1000
##        403        412        429        517        568        569        575
##  2345.1076  4328.1084  1319.2155  2547.7174  1438.1406  1120.5332  2018.0146
##        589        599        603        606        613        636        642
##  1446.8379  2062.6623  2205.6950  1398.6189  2367.2154  2371.5737  1583.8894
##        643        664        682        702        704        718        721
##  2023.1393  2539.0754  6282.7678  2023.1393  1746.2651  2450.9759  6461.2702
##        725        742       1098       1175       1188       1193       1200
##  3095.2468  2099.8254  1851.2819  2143.9132  1392.0030  1799.6596  3170.1603
##       1205       1218       1220       1228       1273       1328       1333
##  1627.6209  2435.0545  1400.5215  1360.9985  2658.8165  2007.6487  1941.4808
##       1356       1378       1384       1392       1414       1427       1429
##  2484.2404  2598.6286  3119.4579  1220.1430  3325.2158  1839.5388  1537.3955
##       1438       1463       1474       1476       1481       1495       1515
##  1082.9128  2540.9241  1008.0477  1795.9095  1775.6021  2774.9510  1612.2607
##       1529       1541       1545       1547       1550       1564       1571
```

```
##  3977.4164  1034.5151  1588.0979  1993.6286   716.9064  1976.6455  3143.6929
##       1586       1602       1610       1621       1625       1656       1665
##  1087.4499  2246.2101  2411.3019  2421.6414  2874.6329  3397.3636  1473.3078
##       1674       1692       1713       1737       1777       1787       1806
##  1259.4860  1180.0839  2212.7719  1946.0443  1471.2252  4877.5874  2667.2786
##       1807       1808       1814       1816       1823       1835       1841
##  2159.8371  6061.5457  2962.5561  8124.7908  3470.7846  3457.3728  1698.7360
##       1867       1874       1882       1891       1892       1913       1920
##  1511.5641  3999.3455  3661.7103   948.6745  2616.3974  4212.1778  4670.5145
##       1923       1942       1956       1960       1968       1990       2003
##  1464.6105  3667.6915  2000.5730  2219.3865  4527.0704  1096.3234  1895.1632
##       2013       2016       2063       2069       2079       2086       2094
##  2128.5517  3231.1576  5125.9117  2720.2134  2667.2786  1136.6623  4826.9090
##       2147       2151       2178       2187       2272       2273       2287
##  4483.6199  1822.3757  2186.6607  1981.1800  1149.2582  2245.8539  2570.2598
##       2289       2301       2307       2337       2346       2354       2473
##  2501.0436  1709.4317  1888.0888  6315.0642  1546.2690  1147.0018  1286.1321
##       2482       2496       2499       2503       2507       2511       2558
##  2536.3870  1954.8913  1751.8495  1133.6152  1861.2904  1960.8725  2603.1644
##       2570       2572       2589       2599       2612       2623       2710
##  2126.7513  1510.9269  1554.3774  2691.6200  1514.8544  1117.8436  2179.6861
##       2712       2727       2766       3595       4239       4646       4659
##  2365.3140  2271.7131  3591.1552  5593.5489  3014.0708  4118.6016  1702.9945
##       4672       4680       4699       4704       4706       4724       4763
##  3333.2771  1027.8979  1477.8436  2708.7554  2691.4413  2624.6387  2173.0702
##       4783       4784       4796       4805       4809       4810       4831
##   790.0476  1821.9197  1160.2349  2049.4305  1723.1245  1710.0689  1590.7875
##       4843       4850       4872       4875       4878       4930       4931
##  9945.2372  4374.8845  1301.2691  1292.5718  1695.8702  2186.4820  1776.0593
##       4935       4937       4945       4952       4977       5026       5031
##  1663.1153  1570.6576  1557.2458  2318.1817  2146.6028  1133.7675  1239.6370
##       5042       5059       5074       5609       5613       5619       5622
##  1411.8532  2007.1914  2148.2257  1526.8785  2487.9905  1082.9141  1233.0211
##       5680       5694       5695       5717       5722       6289       6291
##   950.5771  2391.6052   977.0445  1175.7280  1709.4342  1632.5694  4158.6083
##       6299       6305       6316       6317       6332       6349       6354
##  2676.1281  2724.3484  2847.9880  3331.0447  6184.3289  2618.4788  1519.6254
##       6367       6376       6378       6385       6397       6408       6413
##  7180.2493  3344.8873  1941.4808  3179.4670  2748.9119  2084.3612  1921.6293
##       6419       6434       6442       6449       6454       6461       6463
##  4270.4591  2385.4453  1828.5343  4377.1156  2748.9144  5138.0516  3636.0286
##       6486       6488       6500       6505       6506       6511       6512
##  2380.2723  2080.4337  2179.6848  3583.0938  2179.6873  5303.9303  4437.9370
##       6513       6514       6517       6524       6532       6533       6534
##  3158.9783  5848.3153  2523.7609  3386.0332  3000.1740 10259.9763  2576.6957
##       6537       6552       6557       6570       6573       6582       6590
##  6964.6578  3106.0436  4820.4429  2410.8170  2854.7814  2391.4240  3020.6602
##       6595       6600       6603       6612       6624       6630       6631
##  3397.1849  5708.5478  2093.8455  1917.2710  1795.6298  2841.3696  1796.0857
##       6633       6648       6663       6668       6672       6678       6685
##  2345.1076  3370.7175  4787.9943  3247.0778  5185.0051  2371.5750  2133.3685
##       6686       6700       6701       6704       6748       6775       6779
##  1884.1852  1385.2071  2123.8842  1762.5440  3966.6929  1544.0114  3324.4011
##       6780       6786       6794       6817       6826       6840       6859
```

```
##  5084.9670  9128.6466  4511.0754  6002.6285  3325.2133 10067.2739  3201.5761
##       6873       6875       6879       6896       6900       6903       6938
##  2664.3392  3986.5419  5052.2122  2887.8672  2609.7815  6035.5355  4028.6812
##       6965       6975       7004       7076       7116       7119       7145
##  4347.9573  2431.3057  2235.6944  4390.5274  3324.4011  5435.8113  3139.1294
##       7164       7173       7174       7183       7228       7242       7251
##  8088.8379  2854.7814  4055.1486  2684.8254  1422.6764  3006.7924  1632.1109
##       7283       7289       7300       7882       7920       7929       7964
##  2744.1999  3946.5629  2358.5194  1998.3419  2742.2960  2961.1095  2205.8737
##       8000       8017       8025       8059       8061       8069       8083
##  1917.0923  1457.9921  5949.5150  6183.0569  1226.5802  3945.9270  3258.8680
##       8084       8115       8120       8142       8148       8152       8228
##  2172.2820  2404.8370  1379.0472  2050.6407  3397.6434  2186.4807  3020.0255
##       8243       8284       8312       8313       8332       8360       8383
##  3675.7291  2437.7428  1994.4143  3397.6434  5694.3253  1431.5247  2815.7169
##       8400       8406       8411       8420       8428       8441       8455
##  5007.7960  2484.6964  2417.8926  2437.7428  2173.0689  2411.2755  1670.5447
##       8458       8500       8503       8509       8522       8536       8540
##  2470.8274  2814.9035  3864.1149   902.1769  1563.8617  2040.7320  4213.7742
##       8590       8621       8645       8649       8653       8673       8680
##  1742.5163  2007.1902  1696.1986  1742.5163  1087.4486  3125.8950  1888.5448
##       8715       8747       8774       8783       8879       8882       8893
##  2841.8281  4946.1639   540.6869  1704.8959  4833.2199  2514.2779  5694.3253
##       8907       9002       9095       9132       9133
##  2755.3515  1849.0218  1888.2650   963.8089  2086.5923
```

Vamos a calcular el RMSE.Primero hacemos la diferencias entre los valores reales y los predecidos, luego el residual de la suma y el valor del acierto

```
dif <- data_val_rg$price-data_val_regresion
rmse <- sqrt(mean(dif ^ 2))
rmse
```

```
## [1] 1255.776
```

Vemos que el RSME es una diferencia bastante grande. Pasamos a calcular el acierto

```
residual <- sum(dif^2)
total <- sum((data_val_rg$price - mean(data_val_rg$price)) ^ 2)
acierto_rg <- 1 - (residual / total)
acierto_rg
```

```
## [1] 0.5832167
```

No supervisado: Clustering con k-means

Primero pasamos a ver que las variables sean numericas

```
lapply(data,class)
```

```
## $price
## [1] "numeric"
```

```
##
## $floor_built
## [1] "numeric"
##
## $bathrooms
## [1] "numeric"
##
## $terrace
## [1] "numeric"
##
## $bedrooms
## [1] "numeric"
##
## $postalcode
## [1] "numeric"
##
## $garage_included
## [1] "numeric"
```

Comprobamos si necesitamos escalarlas.

```
summary(data)
```

```
##      price        floor_built      bathrooms         terrace
##  Min.   :  725   Min.   : 30.0   Min.   : 1.000   Min.   :0.0000
##  1st Qu.: 1450   1st Qu.: 80.0   1st Qu.: 1.000   1st Qu.:0.0000
##  Median : 2200   Median :101.0   Median : 2.000   Median :0.0000
##  Mean   : 2698   Mean   :119.6   Mean   : 2.016   Mean   :0.2765
##  3rd Qu.: 3350   3rd Qu.:140.0   3rd Qu.: 2.000   3rd Qu.:1.0000
##  Max.   :25000   Max.   :512.0   Max.   :20.000   Max.   :1.0000
##     bedrooms       postalcode    garage_included
##  Min.   :2.000   Min.   :28001   Min.   :0.0000
##  1st Qu.:2.000   1st Qu.:28003   1st Qu.:0.0000
##  Median :2.000   Median :28006   Median :0.0000
##  Mean   :2.643   Mean   :28006   Mean   :0.1841
##  3rd Qu.:3.000   3rd Qu.:28008   3rd Qu.:0.0000
##  Max.   :6.000   Max.   :28011   Max.   :1.0000
```

Vemos que hay mucha diferencia entre el maximo y el minimo por lo cual sería necesario escalarlo, para tener una mejor vision global

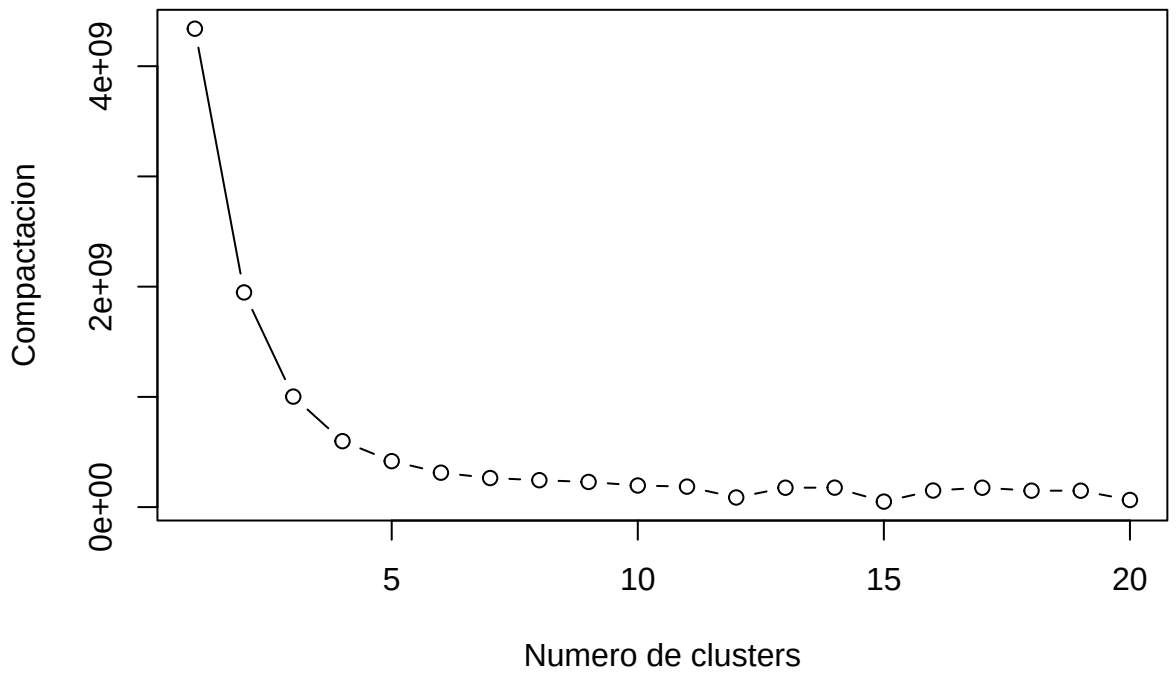
```
data_scaled = scale(data)
summary(data_scaled)
```

```
##      price          floor_built        bathrooms           terrace
##  Min.   :-1.0237   Min.   :-1.4362   Min.   :-0.97777   Min.   :-0.618
##  1st Qu.:-0.6476   1st Qu.:-0.6350   1st Qu.:-0.97777   1st Qu.:-0.618
##  Median :-0.2584   Median :-0.2985   Median :-0.01565   Median :-0.618
##  Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.00000   Mean   : 0.000
##  3rd Qu.: 0.3382   3rd Qu.: 0.3265   3rd Qu.:-0.01565   3rd Qu.: 1.617
##  Max.   :11.5707   Max.   : 6.2877   Max.   :17.30258   Max.   : 1.617
##     bedrooms         postalcode      garage_included
```

```
##  Min.   :-0.7999   Min.   :-1.6429   Min.   :-0.4748
##  1st Qu.:-0.7999   1st Qu.:-0.9334   1st Qu.:-0.4748
##  Median :-0.7999   Median : 0.1309   Median :-0.4748
##  Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.0000
##  3rd Qu.: 0.4441   3rd Qu.: 0.8405   3rd Qu.:-0.4748
##  Max.   : 4.1761   Max.   : 1.9048   Max.   : 2.1045
```

Una vez lo datos bien estructurados, pasamos a calcular el mejor valor de k. Para ello iremos iterando el valor de 1 a 20 para guardar el valor de compatacion en cada iteracion, luego lo graficaremos y veremos a el k que produce un cambio considerable. Inicializamos la variables nstart a 10 para controlar la aleatoridad.

```
v_compac <-0

for(i in 1:20){

  km1<-kmeans(data,center=i,nstar=10)
  v_compac[i] <- km1$tot.withinss

}

par(mfrow = c(1,1))

plot(1:20, v_compac, type = "b",
     xlab = "Numero de clusters",
     ylab = "Compactacion")
```



Observamos que en k=3 y k=4 empieza a ver un cambio significativo, por lo cual escogemos estos valores para K. Pasamos a ver los resultados y comparamos

K=3

```
kmeans3 <- kmeans(data, center =3,nstart= 10)
kmeans3
```

```
## K-means clustering with 3 clusters of sizes 52, 377, 739
##
## Cluster means:
##      price floor_built bathrooms   terrace bedrooms postalcode garage_included
## 1 9088.096   268.13462  3.846154 0.3846154 3.557692   28003.69       0.3269231
## 2 3796.255   149.38992  2.541114 0.2758621 2.811671   28005.33       0.1962865
## 3 1688.304    93.99323  1.619756 0.2692828 2.492558   28005.92       0.1677943
##
## Clustering vector:
##    7   15   16   17   18   24   28   29   39   42   45   47   50   58   60   66
##    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3
##   71   73   76   82   83   95   96   98  107  108  120  122  129  133  136  137
##    3    3    3    3    3    3    3    3    3    3    3    3    3    2    3    3
##  140  144  160  162  164  172  173  189  193  204  207  209  210  222  224  225
##    3    3    3    3    3    2    2    3    3    3    3    2    3    3    1    1
##  226  227  237  240  246  248  250  252  257  266  268  270  284  286  288  315
##    1    2    3    2    3    3    3    3    3    3    3    3    2    1    1    3
##  320  321  330  331  332  343  347  356  366  367  368  373  377  378  382  401
##    3    3    3    3    1    3    3    3    2    3    3    3    3    3    3    3
##  403  412  418  428  429  432  441  442  443  448  449  485  489  499  501  502
##    3    2    3    2    3    1    3    2    3    3    3    3    3    3    3    3
##  509  517  524  533  535  545  550  552  555  566  568  569  572  575  579  589
##    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3
##  590  599  600  603  606  613  628  636  642  643  664  668  673  682  690  693
##    3    3    3    3    3    3    3    3    3    3    3    3    3    2    3    3
##  702  704  705  709  710  713  718  721  725  733  742 1098 1173 1175 1176 1177
##    3    3    3    3    3    3    3    2    3    3    3    3    2    3    3    3
## 1179 1181 1182 1184 1188 1193 1199 1200 1203 1204 1205 1212 1214 1218 1220 1223
##    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3
## 1228 1230 1231 1236 1239 1244 1245 1252 1264 1268 1269 1271 1272 1273 1277 1279
##    3    2    2    3    3    3    3    3    2    3    3    3    2    2    3    3
## 1282 1285 1296 1301 1305 1307 1317 1318 1319 1321 1325 1327 1328 1333 1335 1340
##    3    3    3    3    2    3    2    3    3    3    3    2    2    3    3    3
## 1345 1348 1349 1356 1362 1366 1367 1374 1376 1378 1379 1384 1385 1391 1392 1397
##    3    3    3    3    2    2    3    3    3    3    3    3    2    3    3    3
## 1400 1401 1402 1403 1409 1414 1415 1418 1420 1421 1422 1427 1428 1429 1432 1436
##    3    3    3    2    3    3    3    3    3    2    3    3    2    3    3    3
## 1437 1438 1441 1450 1453 1454 1456 1461 1463 1468 1469 1473 1474 1476 1478 1481
##    3    3    3    3    3    3    3    3    3    2    3    3    3    3    3    3
## 1495 1496 1507 1508 1512 1515 1529 1530 1537 1540 1541 1545 1546 1547 1548 1550
##    2    3    3    3    3    3    3    3    3    3    3    3    2    3    3    3
## 1554 1560 1564 1566 1571 1575 1584 1586 1592 1594 1596 1598 1599 1600 1602 1603
##    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3
## 1605 1610 1621 1622 1623 1625 1627 1629 1630 1631 1639 1643 1656 1665 1670 1671
##    3    3    3    3    3    2    3    3    3    3    3    2    3    3    3    3
## 1672 1674 1687 1692 1693 1695 1700 1710 1713 1716 1722 1724 1725 1727 1729 1733
```

```
##    3    3    3    3    3    3    2    3    3    3    2    3    3    3    3    2
## 1737 1741 1748 1749 1754 1756 1761 1763 1767 1768 1771 1773 1777 1780 1787 1793
##    3    3    3    2    2    2    2    3    2    3    3    2    3    3    2    2
## 1797 1801 1806 1807 1808 1812 1814 1816 1821 1822 1823 1829 1833 1834 1835 1836
##    3    3    3    2    2    3    2    2    2    2    2    2    2    3    2    2
## 1838 1840 1841 1853 1855 1857 1858 1861 1864 1867 1871 1874 1879 1882 1883 1885
##    3    3    3    1    2    3    2    2    2    2    3    2    2    2    3    2
## 1888 1889 1891 1892 1904 1905 1906 1908 1911 1913 1915 1918 1920 1923 1924 1930
##    2    3    3    2    2    2    2    2    2    2    2    2    2    3    3    2
## 1934 1938 1939 1942 1945 1946 1948 1949 1953 1954 1956 1957 1960 1962 1965 1968
##    3    3    3    2    3    2    2    1    3    2    3    2    3    3    3    2
## 1969 1970 1971 1972 1975 1976 1977 1978 1983 1990 1991 1993 2003 2007 2008 2012
##    2    1    2    3    2    3    1    3    3    3    3    3    2    3    2    2
## 2013 2016 2020 2021 2041 2045 2049 2056 2057 2063 2069 2070 2079 2082 2084 2086
##    3    2    2    3    2    3    3    3    3    2    3    2    3    3    2    3
## 2088 2090 2091 2093 2094 2099 2101 2103 2107 2108 2115 2116 2144 2147 2151 2164
##    3    3    3    2    2    2    3    3    3    2    2    2    3    2    3    3
## 2165 2167 2172 2175 2178 2184 2187 2190 2197 2204 2205 2208 2209 2213 2228 2230
##    3    2    3    2    2    3    2    2    2    3    3    2    3    3    2    3
## 2232 2241 2251 2269 2270 2272 2273 2283 2286 2287 2289 2300 2301 2305 2307 2317
##    3    2    3    3    3    3    2    3    3    2    3    3    3    2    3    3
## 2335 2337 2341 2346 2350 2351 2354 2358 2364 2368 2473 2482 2483 2485 2495 2496
##    2    1    3    3    3    3    3    3    3    3    3    3    3    3    3    3
## 2497 2499 2503 2507 2509 2511 2513 2519 2521 2530 2538 2549 2552 2557 2558 2563
##    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3
## 2568 2570 2572 2579 2589 2599 2602 2605 2610 2612 2614 2620 2621 2623 2641 2645
##    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3
## 2661 2662 2670 2682 2689 2710 2712 2727 2739 2744 2746 2747 2751 2764 2766 2768
##    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3
## 2771 3046 3595 4239 4646 4649 4652 4653 4655 4659 4661 4663 4664 4665 4670 4672
##    3    3    3    2    3    3    3    3    3    3    3    3    3    3    2    3
## 4678 4679 4680 4682 4697 4699 4700 4704 4706 4724 4731 4743 4745 4763 4768 4769
##    3    3    3    3    3    3    3    3    3    2    3    3    3    3    2    2
## 4770 4771 4772 4779 4783 4784 4792 4793 4794 4796 4797 4804 4805 4806 4809 4810
##    2    2    2    2    3    3    3    2    2    3    3    3    3    1    3    3
## 4826 4831 4833 4838 4843 4845 4850 4853 4859 4872 4873 4874 4875 4878 4879 4890
##    3    3    3    3    2    2    2    3    3    2    3    3    3    2    3    3
## 4898 4900 4905 4923 4930 4931 4935 4937 4938 4945 4952 4958 4959 4961 4965 4968
##    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3
## 4977 4982 4983 4987 4994 5000 5007 5014 5016 5026 5031 5032 5033 5042 5043 5046
##    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3    1
## 5059 5069 5070 5071 5074 5075 5606 5609 5610 5613 5615 5619 5622 5624 5630 5635
##    3    2    2    3    3    3    3    3    3    3    3    3    3    3    3    3
## 5637 5642 5643 5644 5669 5677 5680 5684 5687 5690 5693 5694 5695 5700 5701 5706
##    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3
## 5712 5715 5717 5719 5722 5724 5726 5736 5737 5742 5743 5749 6229 6235 6240 6246
##    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3    3
## 6273 6277 6278 6279 6282 6288 6289 6291 6299 6305 6308 6316 6317 6319 6327 6329
##    2    2    1    2    3    2    3    2    3    3    3    2    3    3    2    2
## 6330 6331 6332 6336 6349 6350 6354 6363 6367 6376 6377 6378 6379 6384 6385 6387
##    3    2    2    1    3    3    3    2    2    2    2    2    1    3    2    2
## 6389 6397 6398 6400 6402 6408 6413 6418 6419 6426 6430 6432 6434 6436 6442 6448
##    3    3    3    3    3    3    3    3    2    2    3    1    2    1    3    2
## 6449 6452 6454 6458 6461 6463 6465 6468 6471 6475 6481 6482 6484 6486 6488 6496
```

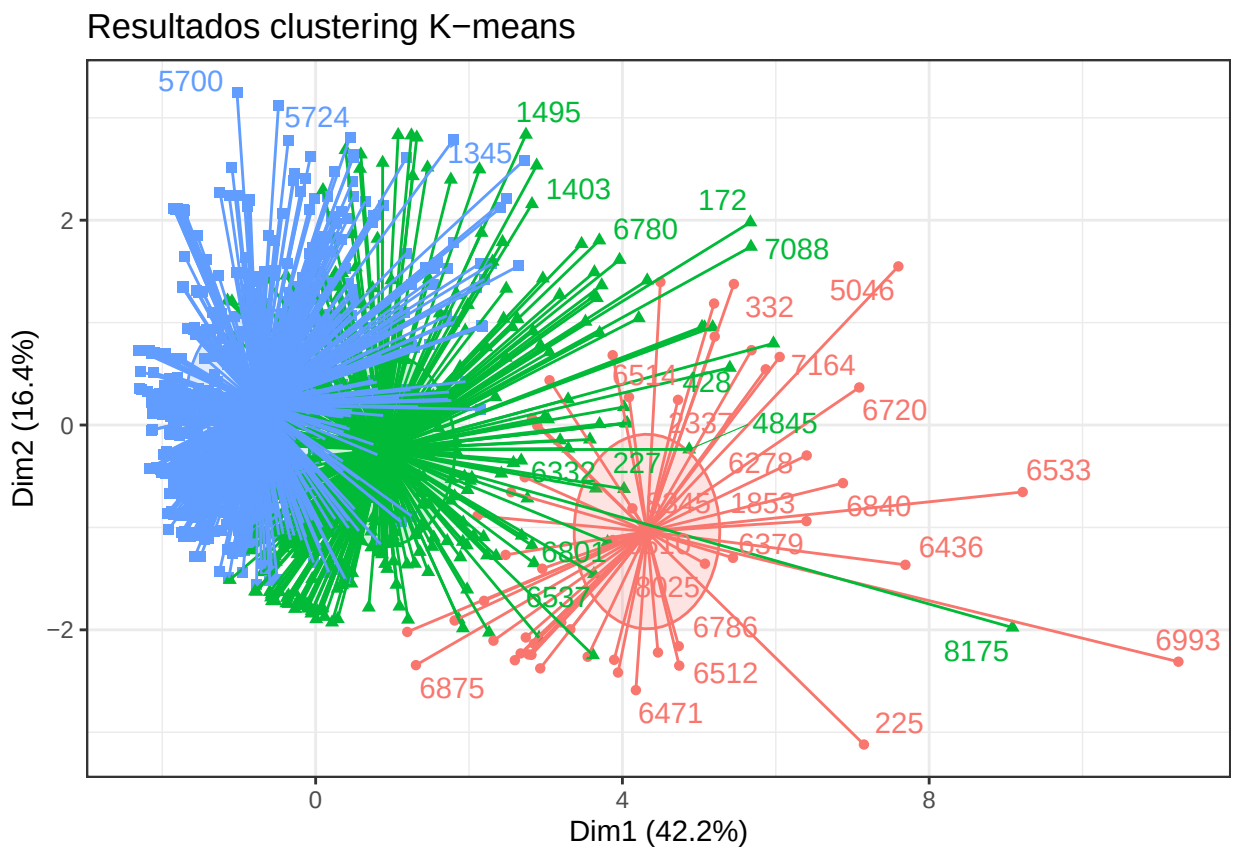
```
##    2    3    2    2    2    3    2    2    1    2    2    3    3    2    2    2
## 6497 6500 6502 6503 6505 6506 6510 6511 6512 6513 6514 6515 6516 6517 6518 6519
##    2    2    2    2    2    2    1    1    1    2    1    3    2    2    3    2
## 6520 6522 6524 6525 6526 6527 6530 6532 6533 6534 6536 6537 6538 6542 6543 6546
##    2    2    2    3    3    2    2    2    1    2    3    2    2    2    2    3
## 6549 6551 6552 6553 6554 6556 6557 6558 6566 6568 6569 6570 6573 6575 6576 6578
##    2    2    2    2    2    2    2    3    2    2    2    2    1    2    2    2
## 6580 6581 6582 6587 6589 6590 6591 6595 6596 6597 6598 6599 6600 6602 6603 6607
##    2    2    2    2    2    2    1    2    2    2    2    2    2    3    3    2
## 6612 6613 6617 6619 6620 6624 6629 6630 6631 6633 6635 6636 6645 6646 6648 6656
##    3    3    3    2    2    3    1    2    2    2    2    2    2    2    2    2
## 6657 6658 6660 6661 6662 6663 6665 6668 6670 6671 6672 6673 6675 6677 6678 6680
##    2    2    2    2    1    1    2    2    1    2    1    2    2    1    2    3
## 6681 6682 6683 6684 6685 6686 6687 6688 6693 6694 6697 6699 6700 6701 6703 6704
##    2    2    2    2    3    2    2    2    2    2    2    2    3    2    2    3
## 6708 6713 6714 6717 6718 6720 6740 6742 6743 6748 6749 6750 6752 6764 6773 6774
##    3    3    1    2    2    1    2    2    2    2    1    2    3    2    2    2
## 6775 6779 6780 6781 6786 6788 6789 6794 6795 6800 6801 6806 6817 6818 6819 6820
##    3    3    2    2    1    3    3    3    2    3    2    2    2    2    2    2
## 6823 6826 6831 6833 6839 6840 6841 6847 6859 6870 6873 6875 6877 6879 6880 6882
##    2    2    2    3    3    1    2    2    3    3    3    1    3    2    3    2
## 6884 6896 6900 6902 6903 6913 6916 6921 6938 6943 6960 6965 6966 6974 6975 6976
##    2    3    2    2    2    3    2    3    2    1    1    2    2    3    2    1
## 6981 6993 7004 7014 7015 7018 7043 7045 7049 7051 7064 7075 7076 7081 7086 7087
##    3    1    3    3    3    3    3    2    3    3    3    3    2    3    2    2
## 7088 7091 7099 7110 7116 7119 7125 7134 7145 7156 7158 7164 7172 7173 7174 7183
##    2    3    3    3    3    2    1    2    3    3    3    1    2    2    2    2
## 7184 7213 7218 7228 7233 7242 7250 7251 7260 7264 7267 7268 7283 7287 7289 7297
##    3    3    3    3    3    3    3    3    3    3    2    3    3    2    3    2
## 7300 7305 7306 7310 7325 7327 7331 7334 7880 7882 7883 7888 7895 7905 7916 7918
##    3    2    2    3    3    3    3    3    3    3    3    3    3    3    2    3
## 7920 7923 7929 7946 7949 7957 7964 7978 7999 8000 8016 8017 8022 8025 8028 8050
##    3    3    3    2    3    1    3    3    3    3    3    3    3    1    2    3
## 8051 8055 8059 8061 8069 8072 8082 8083 8084 8103 8111 8114 8115 8118 8120 8126
##    3    3    2    3    2    3    3    2    3    2    3    3    3    2    3    2
## 8142 8145 8148 8152 8173 8175 8176 8181 8184 8200 8201 8205 8206 8214 8228 8230
##    3    3    2    3    2    2    3    2    3    3    2    2    2    2    2    2
## 8232 8236 8242 8243 8260 8261 8262 8272 8280 8284 8290 8292 8293 8301 8303 8311
##    2    2    2    2    2    2    2    3    2    2    2    2    2    2    1    3
## 8312 8313 8314 8324 8332 8334 8339 8342 8345 8346 8352 8360 8365 8382 8383 8395
##    3    2    3    2    1    2    2    2    1    3    3    3    2    2    2    2
## 8397 8400 8405 8406 8407 8411 8412 8413 8420 8422 8423 8428 8437 8441 8442 8448
##    2    2    2    2    2    3    3    2    2    3    2    3    2    2    2    2
## 8453 8455 8457 8458 8468 8489 8500 8503 8509 8522 8535 8536 8540 8565 8566 8577
##    3    3    3    3    3    3    3    3    3    3    2    2    2    3    3    2
## 8578 8583 8590 8604 8621 8622 8645 8647 8649 8650 8653 8660 8672 8673 8680 8691
##    3    3    3    3    3    2    3    2    3    1    3    3    3    2    2    3
## 8692 8693 8699 8702 8715 8735 8743 8745 8747 8750 8755 8766 8768 8774 8776 8783
##    3    3    3    3    2    2    3    3    2    3    2    3    2    3    3    3
## 8789 8791 8796 8805 8814 8815 8817 8819 8831 8838 8840 8842 8843 8856 8870 8879
##    2    3    2    3    3    3    3    2    3    3    3    3    2    3    3    2
## 8882 8886 8891 8893 8901 8907 8911 8915 8918 8921 8924 8934 8938 8965 8968 8972
##    3    2    3    1    2    3    3    3    3    3    2    3    2    3    2    3
## 8989 8991 8998 9002 9004 9008 9030 9044 9057 9076 9095 9112 9121 9125 9132 9133
```

```
##    3    3    3    3    2    2    3    2    3    3    3    3    3    3    3    3
##
## Within cluster sum of squares by cluster:
## [1] 542226501 273971966 190385294
##  (between_SS / total_SS =  76.8 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

Ahora pasamos a graficarlo para ver los resultados

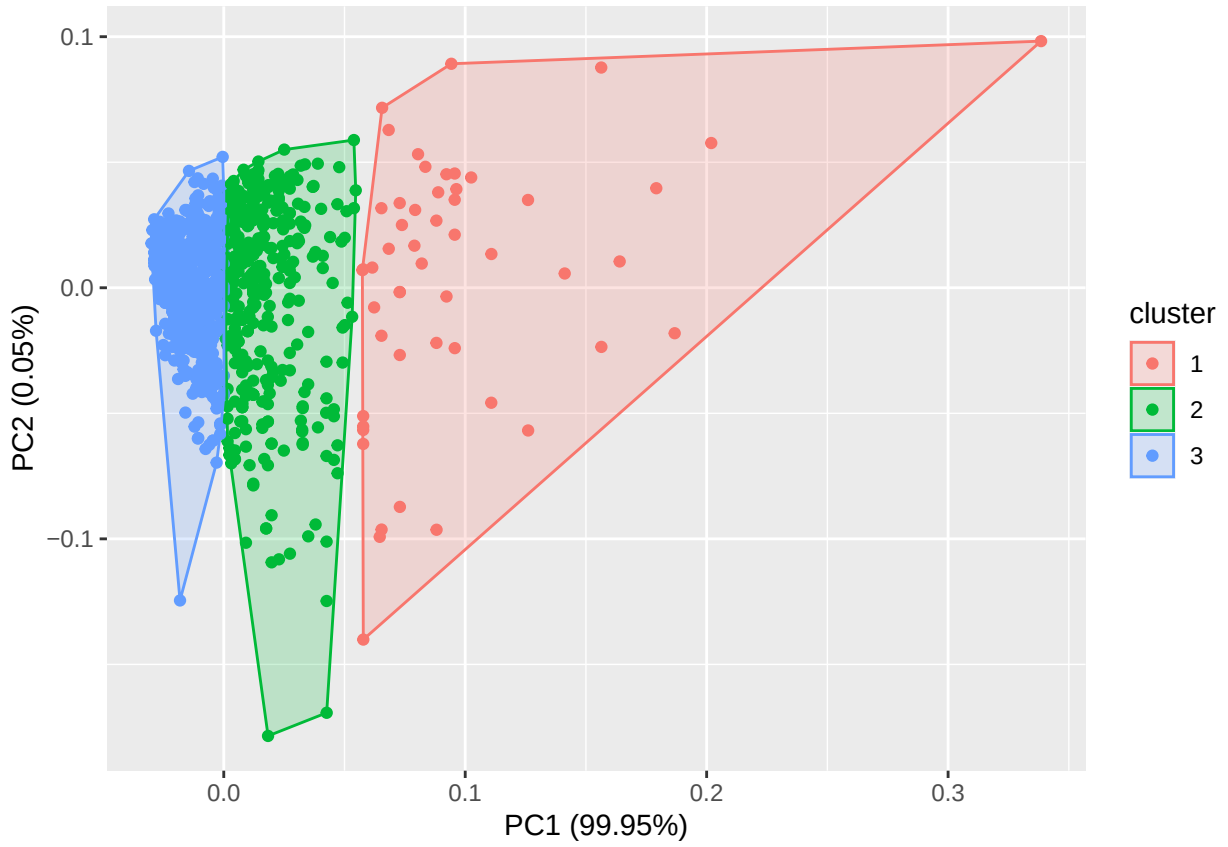
```
fviz_cluster(object = kmeans3, data = data, show.clust.cent = TRUE,
             ellipse.type = "euclid", star.plot = TRUE, repel = TRUE) +
  labs(title = "Resultados clustering K-means") +
  theme_bw() +
  theme(legend.position = "none")
```

```
## Warning: ggrepel: 1132 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```



Tenemos muchos valores, por lo que vamos a realizar otro grafico para verlo mas claro.

```
autoplot(kmeans3, data, frame=TRUE)
```



K=4

```
kmeans4 <- kmeans(data, center =4,nstart= 10)
kmeans4
```

```
## K-means clustering with 4 clusters of sizes 401, 25, 112, 630
##
## Cluster means:
##       price floor_built bathrooms   terrace bedrooms postalcode garage_included
## 1  3173.379   133.52618  2.331671 0.2992519 2.743142   28005.34       0.1845387
## 2 11160.000   296.68000  4.000000 0.5200000 3.680000   28003.68       0.5200000
## 3  5609.545   200.62500  3.089286 0.2232143 3.133929   28005.04       0.2321429
## 4  1542.273    89.35397  1.546032 0.2619048 2.450794   28006.00       0.1619048
##
## Clustering vector:
##    7   15   16   17   18   24   28   29   39   42   45   47   50   58   60   66
##    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4
##   71   73   76   82   83   95   96   98  107  108  120  122  129  133  136  137
##    1    4    4    4    4    4    4    1    4    4    4    4    4    1    4    4
##  140  144  160  162  164  172  173  189  193  204  207  209  210  222  224  225
##    4    1    4    4    1    3    1    4    4    4    4    1    1    4    3    2
##  226  227  237  240  246  248  250  252  257  266  268  270  284  286  288  315
##    2    3    4    1    4    4    1    4    4    4    4    1    1    2    3    4
```

```
##  320  321  330  331  332  343  347  356  366  367  368  373  377  378  382  401
##    4    4    4    4    3    1    4    4    1    4    4    4    1    1    1    4
##  403  412  418  428  429  432  441  442  443  448  449  485  489  499  501  502
##    4    1    4    3    4    3    4    3    4    4    4    1    4    4    4    4
##  509  517  524  533  535  545  550  552  555  566  568  569  572  575  579  589
##    4    4    4    4    4    4    4    1    4    1    4    4    4    4    4    4
##  590  599  600  603  606  613  628  636  642  643  664  668  673  682  690  693
##    4    4    4    4    4    4    4    4    4    4    4    4    4    1    1    1
##  702  704  705  709  710  713  718  721  725  733  742 1098 1173 1175 1176 1177
##    1    4    4    4    4    4    4    1    1    4    4    4    1    4    4    4
## 1179 1181 1182 1184 1188 1193 1199 1200 1203 1204 1205 1212 1214 1218 1220 1223
##    4    4    4    4    4    1    4    4    4    4    4    4    4    4    4    4
## 1228 1230 1231 1236 1239 1244 1245 1252 1264 1268 1269 1271 1272 1273 1277 1279
##    4    1    1    1    4    4    4    4    1    4    4    4    1    1    4    4
## 1282 1285 1296 1301 1305 1307 1317 1318 1319 1321 1325 1327 1328 1333 1335 1340
##    1    4    4    4    1    4    1    1    4    1    4    1    1    4    1    1
## 1345 1348 1349 1356 1362 1366 1367 1374 1376 1378 1379 1384 1385 1391 1392 1397
##    4    4    4    4    1    1    4    4    4    4    4    4    1    4    4    4
## 1400 1401 1402 1403 1409 1414 1415 1418 1420 1421 1422 1427 1428 1429 1432 1436
##    4    4    4    1    4    4    4    4    4    1    4    4    1    4    4    4
## 1437 1438 1441 1450 1453 1454 1456 1461 1463 1468 1469 1473 1474 1476 1478 1481
##    4    4    4    4    4    4    4    4    4    1    4    4    4    4    4    4
## 1495 1496 1507 1508 1512 1515 1529 1530 1537 1540 1541 1545 1546 1547 1548 1550
##    1    4    4    4    4    4    1    4    4    4    4    4    1    4    4    4
## 1554 1560 1564 1566 1571 1575 1584 1586 1592 1594 1596 1598 1599 1600 1602 1603
##    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4
## 1605 1610 1621 1622 1623 1625 1627 1629 1630 1631 1639 1643 1656 1665 1670 1671
##    4    1    4    4    4    3    4    4    4    4    4    1    4    4    1    4
## 1672 1674 1687 1692 1693 1695 1700 1710 1713 1716 1722 1724 1725 1727 1729 1733
##    4    4    4    4    4    1    1    4    4    4    1    4    4    4    4    1
## 1737 1741 1748 1749 1754 1756 1761 1763 1767 1768 1771 1773 1777 1780 1787 1793
##    1    1    4    1    1    1    1    1    1    1    4    3    4    1    3    1
## 1797 1801 1806 1807 1808 1812 1814 1816 1821 1822 1823 1829 1833 1834 1835 1836
##    4    1    4    1    3    4    1    3    1    1    3    3    3    1    1    3
## 1838 1840 1841 1853 1855 1857 1858 1861 1864 1867 1871 1874 1879 1882 1883 1885
##    1    1    1    2    1    4    1    1    1    1    4    3    1    3    4    1
## 1888 1889 1891 1892 1904 1905 1906 1908 1911 1913 1915 1918 1920 1923 1924 1930
##    1    1    4    1    1    1    1    3    1    1    3    1    1    4    4    3
## 1934 1938 1939 1942 1945 1946 1948 1949 1953 1954 1956 1957 1960 1962 1965 1968
##    4    4    4    1    1    1    1    3    4    1    1    1    4    4    4    1
## 1969 1970 1971 1972 1975 1976 1977 1978 1983 1990 1991 1993 2003 2007 2008 2012
##    1    3    3    4    3    1    3    4    4    4    4    4    1    4    1    1
## 2013 2016 2020 2021 2041 2045 2049 2056 2057 2063 2069 2070 2079 2082 2084 2086
##    4    1    3    4    1    4    1    4    4    1    4    1    4    4    3    4
## 2088 2090 2091 2093 2094 2099 2101 2103 2107 2108 2115 2116 2144 2147 2151 2164
##    4    4    4    3    1    1    4    4    4    1    1    1    4    1    4    4
## 2165 2167 2172 2175 2178 2184 2187 2190 2197 2204 2205 2208 2209 2213 2228 2230
##    4    1    4    1    1    4    1    1    1    4    1    1    4    4    1    4
## 2232 2241 2251 2269 2270 2272 2273 2283 2286 2287 2289 2300 2301 2305 2307 2317
##    4    1    1    1    4    4    1    4    4    1    4    4    4    1    4    4
## 2335 2337 2341 2346 2350 2351 2354 2358 2364 2368 2473 2482 2483 2485 2495 2496
##    1    2    4    4    1    4    4    4    4    4    4    4    4    4    4    4
## 2497 2499 2503 2507 2509 2511 2513 2519 2521 2530 2538 2549 2552 2557 2558 2563
##    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4
```

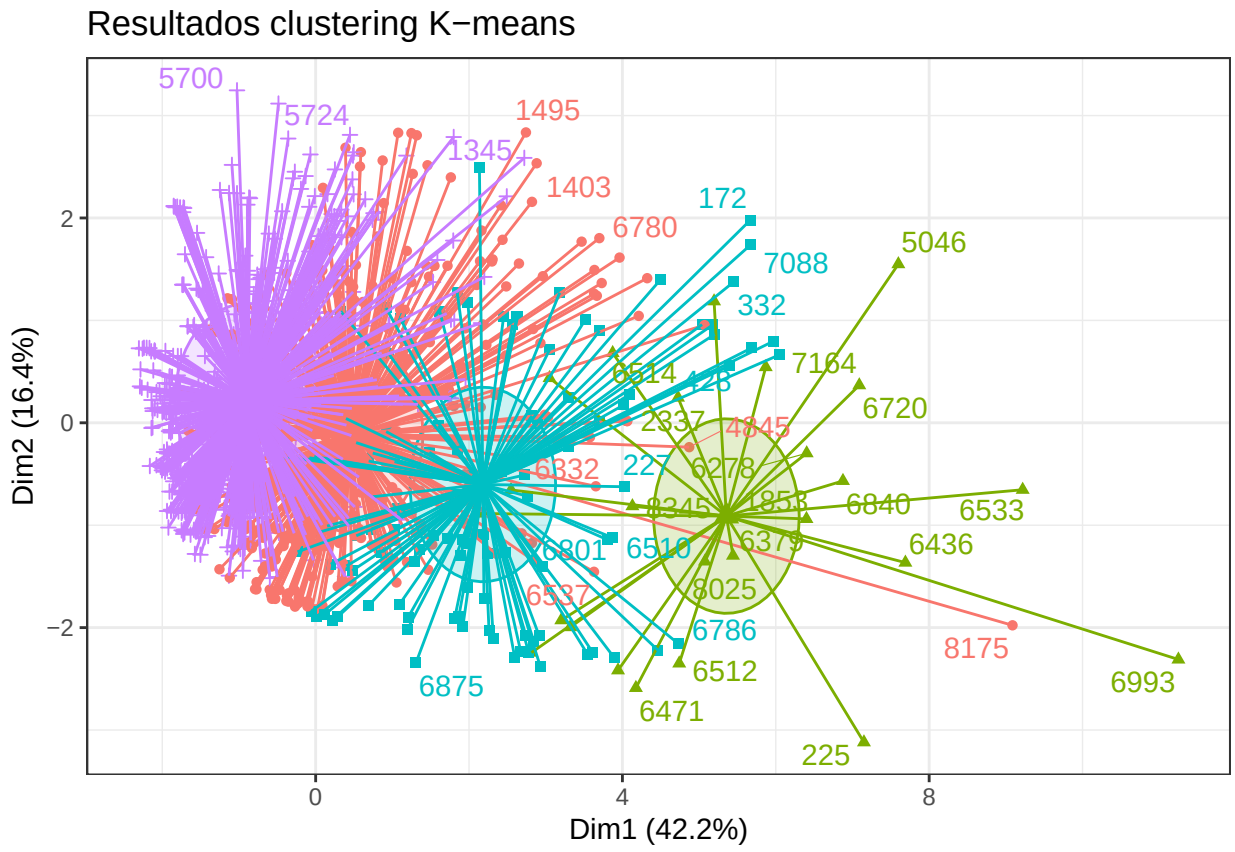
```
## 2568 2570 2572 2579 2589 2599 2602 2605 2610 2612 2614 2620 2621 2623 2641 2645
##    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4
## 2661 2662 2670 2682 2689 2710 2712 2727 2739 2744 2746 2747 2751 2764 2766 2768
##    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4
## 2771 3046 3595 4239 4646 4649 4652 4653 4655 4659 4661 4663 4664 4665 4670 4672
##    4    4    4    1    1    4    4    4    4    4    4    4    4    4    1    1
## 4678 4679 4680 4682 4697 4699 4700 4704 4706 4724 4731 4743 4745 4763 4768 4769
##    1    4    4    4    4    4    4    4    4    1    4    4    4    4    1    1
## 4770 4771 4772 4779 4783 4784 4792 4793 4794 4796 4797 4804 4805 4806 4809 4810
##    1    1    1    1    4    4    4    1    1    4    4    4    4    3    4    4
## 4826 4831 4833 4838 4843 4845 4850 4853 4859 4872 4873 4874 4875 4878 4879 4890
##    4    1    4    4    3    1    1    4    4    1    1    4    4    1    1    4
## 4898 4900 4905 4923 4930 4931 4935 4937 4938 4945 4952 4958 4959 4961 4965 4968
##    4    4    4    4    4    4    4    4    4    4    4    4    1    1    4    4
## 4977 4982 4983 4987 4994 5000 5007 5014 5016 5026 5031 5032 5033 5042 5043 5046
##    4    4    1    4    4    4    4    4    4    4    4    4    4    4    4    2
## 5059 5069 5070 5071 5074 5075 5606 5609 5610 5613 5615 5619 5622 5624 5630 5635
##    4    1    1    4    4    4    4    4    4    4    4    4    4    4    4    4
## 5637 5642 5643 5644 5669 5677 5680 5684 5687 5690 5693 5694 5695 5700 5701 5706
##    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4    4
## 5712 5715 5717 5719 5722 5724 5726 5736 5737 5742 5743 5749 6229 6235 6240 6246
##    4    4    4    4    4    4    4    4    4    4    4    4    1    4    4    4
## 6273 6277 6278 6279 6282 6288 6289 6291 6299 6305 6308 6316 6317 6319 6327 6329
##    1    1    2    1    4    3    4    1    1    1    4    1    1    4    1    1
## 6330 6331 6332 6336 6349 6350 6354 6363 6367 6376 6377 6378 6379 6384 6385 6387
##    1    3    1    2    4    4    4    3    3    1    1    1    2    4    3    3
## 6389 6397 6398 6400 6402 6408 6413 6418 6419 6426 6430 6432 6434 6436 6442 6448
##    1    4    4    4    4    4    4    1    1    1    4    3    1    2    4    1
## 6449 6452 6454 6458 6461 6463 6465 6468 6471 6475 6481 6482 6484 6486 6488 6496
##    1    4    1    1    3    4    1    1    2    1    1    4    1    1    1    1
## 6497 6500 6502 6503 6505 6506 6510 6511 6512 6513 6514 6515 6516 6517 6518 6519
##    1    1    1    1    3    1    3    3    2    1    2    1    1    1    1    1
## 6520 6522 6524 6525 6526 6527 6530 6532 6533 6534 6536 6537 6538 6542 6543 6546
##    1    1    1    4    4    1    1    1    2    1    1    1    1    3    3    4
## 6549 6551 6552 6553 6554 6556 6557 6558 6566 6568 6569 6570 6573 6575 6576 6578
##    1    3    1    1    3    1    3    4    3    3    1    1    3    1    3    1
## 6580 6581 6582 6587 6589 6590 6591 6595 6596 6597 6598 6599 6600 6602 6603 6607
##    3    1    1    1    1    3    3    1    3    3    3    3    3    4    4    3
## 6612 6613 6617 6619 6620 6624 6629 6630 6631 6633 6635 6636 6645 6646 6648 6656
##    1    4    4    1    3    4    3    1    1    1    1    1    1    1    3    1
## 6657 6658 6660 6661 6662 6663 6665 6668 6670 6671 6672 6673 6675 6677 6678 6680
##    3    3    3    1    3    3    1    1    3    3    2    3    1    2    1    1
## 6681 6682 6683 6684 6685 6686 6687 6688 6693 6694 6697 6699 6700 6701 6703 6704
##    1    1    1    1    1    1    3    1    1    1    1    1    4    1    1    4
## 6708 6713 6714 6717 6718 6720 6740 6742 6743 6748 6749 6750 6752 6764 6773 6774
##    4    1    3    1    3    2    1    3    1    1    3    1    4    1    1    3
## 6775 6779 6780 6781 6786 6788 6789 6794 6795 6800 6801 6806 6817 6818 6819 6820
##    4    1    1    1    3    1    1    1    1    1    3    1    3    1    1    1
## 6823 6826 6831 6833 6839 6840 6841 6847 6859 6870 6873 6875 6877 6879 6880 6882
##    3    1    1    4    4    2    1    3    1    1    1    3    4    1    4    3
## 6884 6896 6900 6902 6903 6913 6916 6921 6938 6943 6960 6965 6966 6974 6975 6976
##    1    1    1    3    1    1    1    4    1    3    3    1    1    4    1    3
## 6981 6993 7004 7014 7015 7018 7043 7045 7049 7051 7064 7075 7076 7081 7086 7087
##    4    2    4    4    4    4    4    1    4    4    4    4    1    4    1    1
```

```
## 7088 7091 7099 7110 7116 7119 7125 7134 7145 7156 7158 7164 7172 7173 7174 7183
##    3    4    4    1    4    1    2    3    4    1    4    2    1    1    1    1
## 7184 7213 7218 7228 7233 7242 7250 7251 7260 7264 7267 7268 7283 7287 7289 7297
##    1    1    1    4    4    1    4    4    4    1    3    4    4    1    1    1
## 7300 7305 7306 7310 7325 7327 7331 7334 7880 7882 7883 7888 7895 7905 7916 7918
##    4    1    1    1    4    4    4    4    1    4    4    4    4    4    1    4
## 7920 7923 7929 7946 7949 7957 7964 7978 7999 8000 8016 8017 8022 8025 8028 8050
##    4    4    4    1    4    3    4    4    4    4    4    4    4    2    1    1
## 8051 8055 8059 8061 8069 8072 8082 8083 8084 8103 8111 8114 8115 8118 8120 8126
##    4    4    1    4    1    4    4    3    4    1    4    4    1    3    1    1
## 8142 8145 8148 8152 8173 8175 8176 8181 8184 8200 8201 8205 8206 8214 8228 8230
##    4    4    3    1    1    1    4    3    1    4    1    1    1    1    1    3
## 8232 8236 8242 8243 8260 8261 8262 8272 8280 8284 8290 8292 8293 8301 8303 8311
##    1    3    1    1    3    1    1    4    1    1    1    3    1    1    3    4
## 8312 8313 8314 8324 8332 8334 8339 8342 8345 8346 8352 8360 8365 8382 8383 8395
##    4    1    1    1    2    3    3    1    2    4    4    4    1    3    3    1
## 8397 8400 8405 8406 8407 8411 8412 8413 8420 8422 8423 8428 8437 8441 8442 8448
##    3    1    3    1    1    1    4    1    1    1    1    1    1    1    3    1
## 8453 8455 8457 8458 8468 8489 8500 8503 8509 8522 8535 8536 8540 8565 8566 8577
##    4    4    4    1    4    4    1    1    4    4    1    1    1    4    4    1
## 8578 8583 8590 8604 8621 8622 8645 8647 8649 8650 8653 8660 8672 8673 8680 8691
##    4    4    4    4    4    1    4    1    4    3    4    1    4    1    1    4
## 8692 8693 8699 8702 8715 8735 8743 8745 8747 8750 8755 8766 8768 8774 8776 8783
##    4    4    4    4    3    1    4    1    1    4    1    4    1    4    4    4
## 8789 8791 8796 8805 8814 8815 8817 8819 8831 8838 8840 8842 8843 8856 8870 8879
##    1    4    1    4    1    4    4    1    4    4    4    4    1    4    4    1
## 8882 8886 8891 8893 8901 8907 8911 8915 8918 8921 8924 8934 8938 8965 8968 8972
##    4    1    4    2    1    4    1    4    4    4    3    4    1    4    1    4
## 8989 8991 8998 9002 9004 9008 9030 9044 9057 9076 9095 9112 9121 9125 9132 9133
##    4    4    4    4    1    1    4    1    1    4    4    4    4    4    4    4
##
## Within cluster sum of squares by cluster:
## [1] 119938239 327314347 120966510  97929284
##  (between_SS / total_SS =  84.7 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

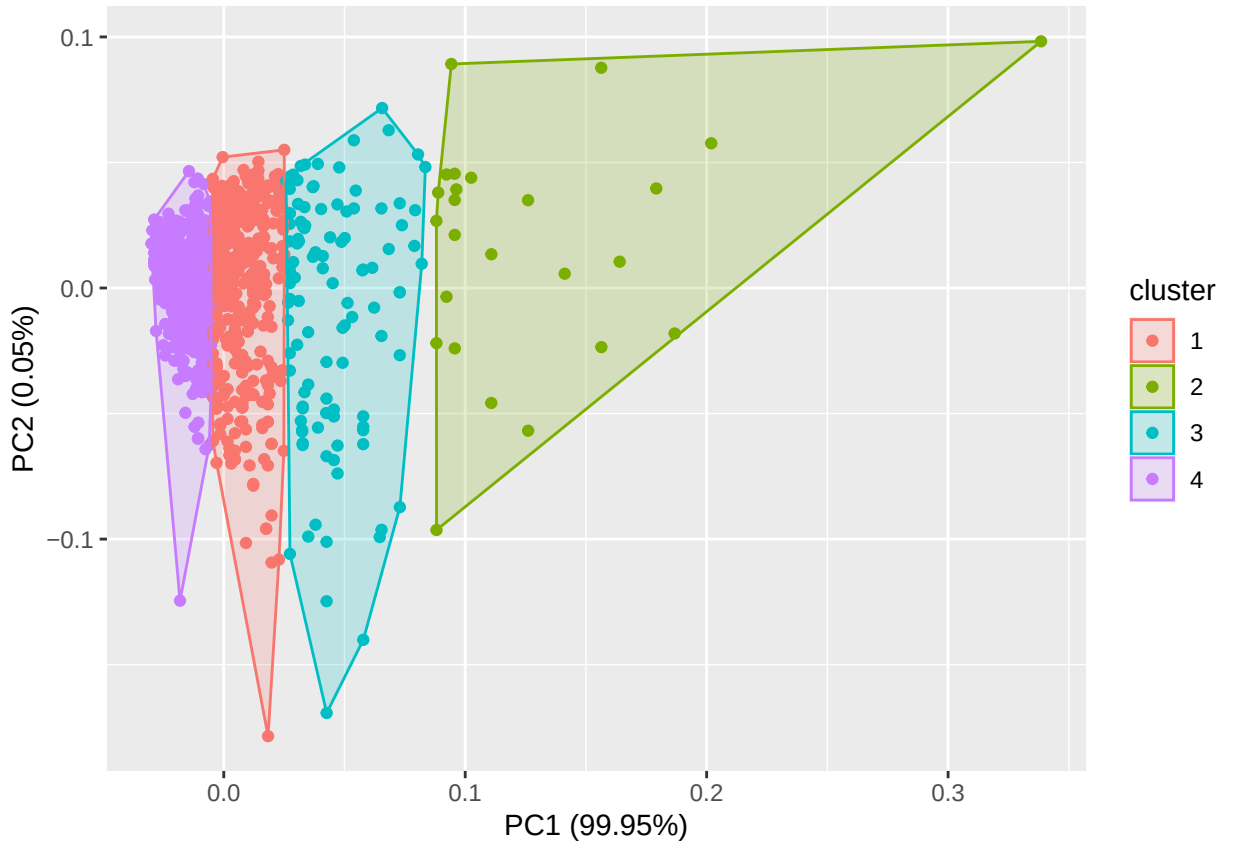
Ahora pasamos a graficarlo para ver los resultados, como hemos hecho anteriormente

```
fviz_cluster(object = kmeans4, data = data, show.clust.cent = TRUE,
             ellipse.type = "euclid", star.plot = TRUE, repel = TRUE) +
  labs(title = "Resultados clustering K-means") +
  theme_bw() +
  theme(legend.position = "none")
```

```
## Warning: ggrepel: 1132 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps
```




```
autoplot(kmeans4, data, frame=TRUE)
```



Obsevarmos que con K=4 tenemos todos los cluster con un gran numero de valores aunque al graficarlos vemos que están muy juntos por la zona media.

Pasamos el Clustering jerarquico

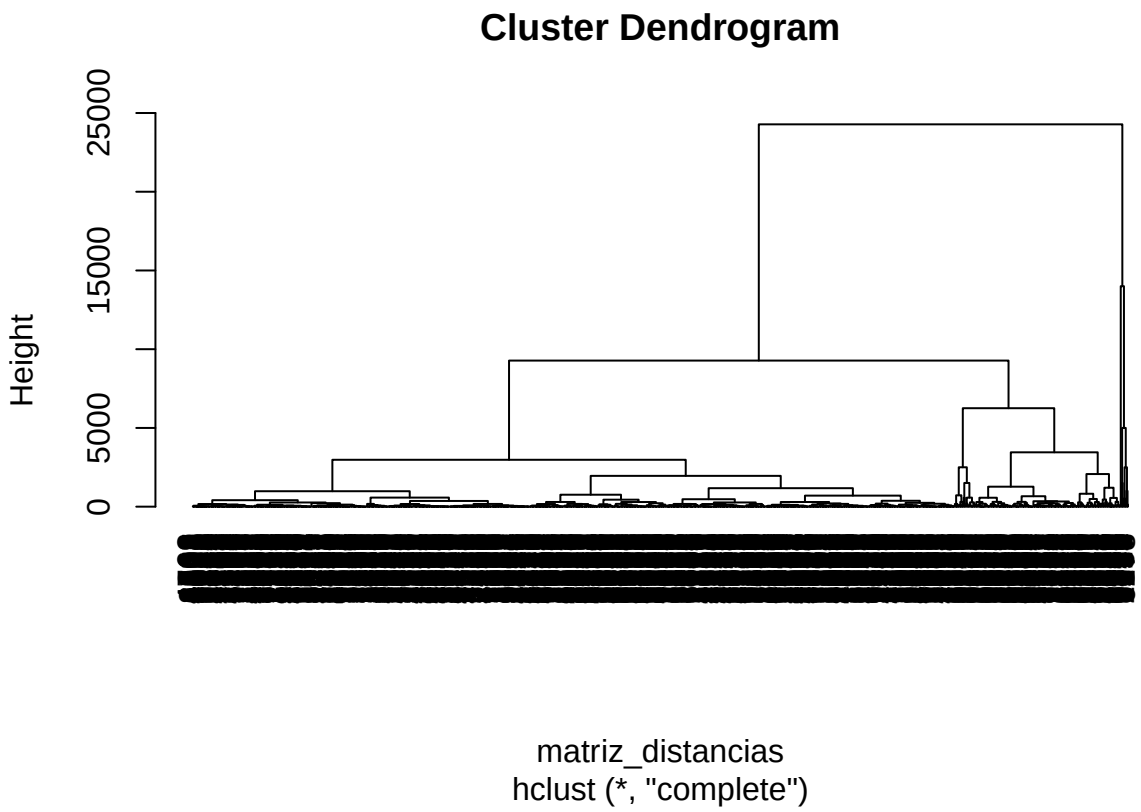
Construimos el dendograma

```
matriz_distancias <-dist(data)
den1 = hclust(matriz_distancias, method = "complete")
summary(den1)
```

```
##             Length Class  Mode
## merge       2334   -none- numeric
## height      1167   -none- numeric
## order       1168   -none- numeric
## labels      1168   -none- character
## method         1   -none- character
## call           3   -none- call
## dist.method    1   -none- character
```

Pasamos a visualizarlo

```
plot(den1,hang = -10)
```



Decidimos cortar según el numero de clusters

```
cortado_den1<-cutree(den1,k=4)
```

Pintamos el grafico para verlo mas claro

```
#Descomentar para ver los resultados. Se ha tenido que comentar debido a que el nivel de carga es super
#fviz_dend(x = den1, cex = 0.8, lwd = 0.8, k = 4,hang = -10,k_colors = c("red", "green3", "blue", "mage
```

Y comparamos con k-means

```
table(kmeans4$cluster,cortado_den1)
```

```
##    cortado_den1
##       1   2   3   4
##   1 321  80   0   0
##   2   0  15   9   1
##   3   0 112   0   0
##   4 630   0   0   0
```