Lab Week 1: Example responses

Code ▾

1 R programming

1.1 File I/O

Reading a dataset

a. Download the `Cereal.csv` file from the Canvas page and use the `read.csv` command to read in the csv file into `R` and assign it to the object called `cereal`.

Solution

▼ Code

```
library(readr)
library(tidyverse)
cereal <- read.csv("Cereal.csv", header = TRUE)
###cereal_df # in HTML file, prints out full data frame -
cereal_tbl<- read_csv("Cereal.csv")
cereal_tbl # in HTML file, only prints out first 10 rows -
```

```
# A tibble: 77 × 16
   name          mfr   type  calor…¹ protein   fat sodium fiber
carbo sugars potass
   <chr>         <chr> <chr>   <dbl>   <dbl> <dbl>  <dbl> <dbl>
<dbl>  <dbl>  <dbl>
 1 100%_Bran     N     C          70       4     1    130  10
5         6     280
 2 100%_Natu… Q     C         120       3     5     15   2
8         8     135
 3 All-Bran      K     C          70       4     1    260   9
7         5     320
 4 All-Bran_… K     C          50       4     0    140  14
8         0     330
 5 Almond_De… R     C         110       2     2    200   1
14         8     -1
 6 Apple_Cin… G     C         110       2     2    180   1.5
10.5       10     70
 7 Apple_Jac… K     C         110       2     0    125   1
11         14     30
```

```
 8 Basic_4    G     C          130        3     2    210   2
18         8    100
 9 Bran_Chex  R     C           90        2     1    200   4
15         6    125
10 Bran_Flak… P     C           90        3     0    210   5
13         5    190
# … with 67 more rows, 5 more variables: vitamins <dbl>, shelf
<dbl>,
#   weight <dbl>, cups <dbl>, rating <dbl>, and abbreviated
variable name
#   ¹calories
```

1.2 Data Types

Data frames

a. There should be a default dataset in `R` called `cereal`. Use the `head` function to inspect the first few lines of the data frame and use `class` to check that `cereal` is in fact a data frame.

Solution

▼ Code

```
### Base R
head(cereal)
```

```
                       name mfr type calories protein fat
sodium fiber carbo
1                 100%_Bran   N    C       70       4   1
130  10.0   5.0
2         100%_Natural_Bran   Q    C      120       3   5
15   2.0   8.0
3                  All-Bran   K    C       70       4   1
260   9.0   7.0
4 All-Bran_with_Extra_Fiber   K    C       50       4   0
140  14.0   8.0
5            Almond_Delight   R    C      110       2   2
200   1.0  14.0
6   Apple_Cinnamon_Cheerios   G    C      110       2   2
180   1.5  10.5
  sugars potass vitamins shelf weight cups   rating
1      6    280       25     3      1 0.33 68.40297
2      8    135        0     3      1 1.00 33.98368
3      5    320       25     3      1 0.33 59.42551
4      0    330       25     3      1 0.50 93.70491
5      8     -1       25     3      1 0.75 34.38484
```

```
6     10     70       25     1       1 0.75 29.50954
```

▼ Code

```
cereal_tbl |> head(7) # using pipe
```

```
# A tibble: 7 × 16
  name         mfr   type   calor…¹ protein   fat sodium fiber
carbo sugars potass
  <chr>        <chr> <chr>    <dbl>   <dbl> <dbl>  <dbl> <dbl>
<dbl>  <dbl>  <dbl>
1 100%_Bran    N     C           70       4     1    130   10
5         6    280
2 100%_Natur… Q     C          120       3     5     15    2
8         8    135
3 All-Bran     K     C           70       4     1    260    9
7         5    320
4 All-Bran_w… K     C           50       4     0    140   14
8         0    330
5 Almond_Del… R     C          110       2     2    200    1
14         8     -1
6 Apple_Cinn… G     C          110       2     2    180    1.5
10.5      10     70
7 Apple_Jacks K     C          110       2     0    125    1
11        14     30
# … with 5 more variables: vitamins <dbl>, shelf <dbl>, weight
<dbl>,
#   cups <dbl>, rating <dbl>, and abbreviated variable name ¹
calories
```

▼ Code

```
cereal_tbl |> class() # tells us this is a tibble
```

```
[1] "spec_tbl_df" "tbl_df"      "tbl"         "data.frame"
```

b. What are the column names of the cereal data frame? How many rows are there? (`dim` and `nrow`)

Solution

▼ Code

```
cereal_tbl |> colnames()
```

```
 [1] "name"     "mfr"      "type"     "calories" "protein"
```

```
"fat"
 [7] "sodium"   "fiber"    "carbo"    "sugars"   "potass"
"vitamins"
[13] "shelf"    "weight"   "cups"     "rating"
```

▼ Code

```
cereal_tbl |> dim()
```

```
[1] 77 16
```

▼ Code

```
cereal_tbl |> nrow()
```

```
[1] 77
```

▼ Code

```
dim(cereal)
```

```
[1] 77 16
```

▼ Code

```
nrow(cereal)
```

```
[1] 77
```

c. Extract the `calories` column using the `$` operator and using the `[[` operator.

Solution

▼ Code

```
### Some 'tidy' ways
Cal <- cereal_tbl %>% select(calories) #tibble with one co
Cal <- cereal_tbl %>% pull(calories) #pull out the column

### Base R
AlternativeCal<-cereal[["calories"]]
acal <- cereal$calories
identical(AlternativeCal, acal)
```

```
[1] TRUE
```

▼ Code

```
class(cereal["calories"])
```

```
[1] "data.frame"
```

▼ Code

```
class(cereal[["calories"]])
```

```
[1] "integer"
```

d. Extract rows 1 to 10 from the `cereal` data frame.

Solution

▼ Code

```
### Base R
cereal[1:10,]
```

```
                        name mfr type calories protein fat
sodium fiber carbo
1                  100%_Bran   N    C       70       4   1
130  10.0   5.0
2          100%_Natural_Bran   Q    C      120       3   5
15   2.0   8.0
3                   All-Bran   K    C       70       4   1
260   9.0   7.0
4  All-Bran_with_Extra_Fiber   K    C       50       4   0
140  14.0   8.0
5             Almond_Delight   R    C      110       2   2
200   1.0  14.0
6    Apple_Cinnamon_Cheerios   G    C      110       2   2
180   1.5  10.5
7                Apple_Jacks   K    C      110       2   0
125   1.0  11.0
8                    Basic_4   G    C      130       3   2
210   2.0  18.0
9                  Bran_Chex   R    C       90       2   1
200   4.0  15.0
10               Bran_Flakes   P    C       90       3   0
210   5.0  13.0
   sugars potass vitamins shelf weight cups   rating
```

```
1       6    280       25      3    1.00 0.33 68.40297
2       8    135        0      3    1.00 1.00 33.98368
3       5    320       25      3    1.00 0.33 59.42551
4       0    330       25      3    1.00 0.50 93.70491
5       8     -1       25      3    1.00 0.75 34.38484
6      10     70       25      1    1.00 0.75 29.50954
7      14     30       25      2    1.00 1.00 33.17409
8       8    100       25      3    1.33 0.75 37.03856
9       6    125       25      1    1.00 0.67 49.12025
10      5    190       25      3    1.00 0.67 53.31381
```

▼ Code

```
### Tidyverse
cereal_tbl %>% slice(1:10)
```

```
# A tibble: 10 × 16
   name        mfr   type  calor…¹ protein   fat sodium fiber
carbo sugars potass
   <chr>       <chr> <chr>   <dbl>   <dbl> <dbl>  <dbl> <dbl>
<dbl>  <dbl>  <dbl>
 1 100%_Bran   N     C          70       4     1    130  10
5        6    280
 2 100%_Natu… Q     C         120       3     5     15   2
8        8    135
 3 All-Bran    K     C          70       4     1    260   9
7        5    320
 4 All-Bran_… K     C          50       4     0    140  14
8        0    330
 5 Almond_De… R     C         110       2     2    200   1
14        8     -1
 6 Apple_Cin… G     C         110       2     2    180   1.5
10.5      10     70
 7 Apple_Jac… K     C         110       2     0    125   1
11       14     30
 8 Basic_4     G     C         130       3     2    210   2
18        8    100
 9 Bran_Chex   R     C          90       2     1    200   4
15        6    125
10 Bran_Flak… P     C          90       3     0    210   5
13        5    190
# … with 5 more variables: vitamins <dbl>, shelf <dbl>, weight
<dbl>,
#   cups <dbl>, rating <dbl>, and abbreviated variable name ¹
calories
```

e. Make a new data frame called `Kelloggs` that only contains rows that belongs to manufacturer, Kelloggs (when `mfr` takes the value `"K"`).

Solution

▼ Code

```
### Base R
Kelloggs <- subset(cereal, mfr == "K")
head(Kelloggs)
```

```
                        name mfr type calories protein fat
sodium fiber carbo
3                   All-Bran   K    C       70       4   1
260     9     7
4  All-Bran_with_Extra_Fiber   K    C       50       4   0
140    14     8
7                Apple_Jacks   K    C      110       2   0
125     1    11
17               Corn_Flakes   K    C      100       2   0
290     1    21
18                 Corn_Pops   K    C      110       1   0
90     1    13
20         Cracklin'_Oat_Bran   K    C      110       3   3
140     4    10
   sugars potass vitamins shelf weight cups   rating
3       5    320       25     3      1 0.33 59.42551
4       0    330       25     3      1 0.50 93.70491
7      14     30       25     2      1 1.00 33.17409
17      2     35       25     1      1 1.00 45.86332
18     12     20       25     2      1 1.00 35.78279
20      7    160       25     3      1 0.50 40.44877
```

▼ Code

```
Kelloggs.2 <- cereal[cereal$mfr == "K", -2] #removes 2nd c
head(Kelloggs.2)
```

```
                        name type calories protein fat sodium
fiber carbo
3                   All-Bran    C       70       4   1    260
9     7
4  All-Bran_with_Extra_Fiber    C       50       4   0    140
14     8
7                Apple_Jacks    C      110       2   0    125
1    11
17               Corn_Flakes    C      100       2   0    290
1    21
```

```
18                 Corn_Pops    C      110        1    0      90
1    13
20        Cracklin'_Oat_Bran    C      110        3    3     140
4    10
   sugars potass vitamins shelf weight cups   rating
3       5    320       25     3      1 0.33 59.42551
4       0    330       25     3      1 0.50 93.70491
7      14     30       25     2      1 1.00 33.17409
17      2     35       25     1      1 1.00 45.86332
18     12     20       25     2      1 1.00 35.78279
20      7    160       25     3      1 0.50 40.44877
```

▼ Code

```
### Base R splitting
cereal.splitted <- split(cereal, cereal$mfr) #list of 7 it
Kelloggs.3 <- cereal.splitted["K"]
Kelloggs.4 <- cereal.splitted[["K"]]
identical(Kelloggs, Kelloggs.4)
```

```
[1] TRUE
```

▼ Code

```
### Tidyverse way
kelloggs_tbl <- cereal_tbl %>% filter(mfr == "K") #tidy wa
kelloggs_tbl <- cereal_tbl %>% filter(mfr == "K") %>% sele
```

Factors

a. Load the `Cereal` data again with the `read.csv` command again. This time, use the optional argument, `stringsAsFactors = TRUE`.
b. The `mfr` and `type` columns are now factors. Check that this is true.

Solution

▼ Code

```
cereal <- read_csv("Cereal.csv")
```

```
Rows: 77 Columns: 16
── Column specification
────────────────────────────────────────────────────────
Delimiter: ","
chr  (3): name, mfr, type
dbl (13): calories, protein, fat, sodium, fiber, carbo,
```

```
sugars, potass, vita...

ℹ Use `spec()` to retrieve the full column specification for
this data.
ℹ Specify the column types or set `show_col_types = FALSE` to
quiet this message.
```

▼ Code

```
cereal.with.factors <- read.csv("Cereal.csv", stringsAsFac
cereal.with.factors
```

```
                                    name mfr type calories
protein fat sodium
1                              100%_Bran   N    C       70
4   1    130
2                      100%_Natural_Bran   Q    C      120
3   5     15
3                               All-Bran   K    C       70
4   1    260
4              All-Bran_with_Extra_Fiber   K    C       50
4   0    140
5                         Almond_Delight   R    C      110
2   2    200
6                Apple_Cinnamon_Cheerios   G    C      110
2   2    180
7                            Apple_Jacks   K    C      110
2   0    125
8                                Basic_4   G    C      130
3   2    210
9                              Bran_Chex   R    C       90
2   1    200
10                           Bran_Flakes   P    C       90
3   0    210
11                          Cap'n'Crunch   Q    C      120
1   2    220
12                              Cheerios   G    C      110
6   2    290
13                 Cinnamon_Toast_Crunch   G    C      120
1   3    210
14                              Clusters   G    C      110
3   2    140
15                           Cocoa_Puffs   G    C      110
1   1    180
16                             Corn_Chex   R    C      110
2   0    280
17                           Corn_Flakes   K    C      100
```

```
2   0    290
18                                  Corn_Pops   K    C       110
1   0     90
19                              Count_Chocula   G    C       110
1   1    180
20                         Cracklin'_Oat_Bran   K    C       110
3   3    140
21                     Cream_of_Wheat_(Quick)   N    H       100
3   0     80
22                                    Crispix   K    C       110
2   0    220
23                     Crispy_Wheat_&_Raisins   G    C       100
2   1    140
24                                Double_Chex   R    C       100
2   0    190
25                                Froot_Loops   K    C       110
2   1    125
26                             Frosted_Flakes   K    C       110
1   0    200
27                         Frosted_Mini-Wheats   K    C       100
3   0      0
28 Fruit_&_Fibre_Dates,_Walnuts,_and_Oats   P    C       120
3   2    160
29                               Fruitful_Bran   K    C       120
3   0    240
30                              Fruity_Pebbles   P    C       110
1   1    135
31                                Golden_Crisp   P    C       100
2   0     45
32                              Golden_Grahams   G    C       110
1   1    280
33                           Grape_Nuts_Flakes   P    C       100
3   1    140
34                                  Grape-Nuts   P    C       110
3   0    170
35                          Great_Grains_Pecan   P    C       120
3   3     75
36                             Honey_Graham_Ohs   Q    C       120
1   2    220
37                           Honey_Nut_Cheerios   G    C       110
3   1    250
38                                  Honey-comb   P    C       110
1   0    180
39                  Just_Right_Crunchy__Nuggets   K    C       110
2   1    170
40                       Just_Right_Fruit_&_Nut   K    C       140
3   1    170
41                                         Kix   G    C       110
```

```
2   1    260
42                                  Life   Q    C      100
4   2    150
43                          Lucky_Charms   G    C      110
2   1    180
44                                 Maypo   A    H      100
4   1      0
45       Muesli_Raisins,_Dates,_&_Almonds   R    C      150
4   3     95
46      Muesli_Raisins,_Peaches,_&_Pecans   R    C      150
4   3    150
47                  Mueslix_Crispy_Blend   K    C      160
3   2    150
48                  Multi-Grain_Cheerios   G    C      100
2   1    220
49                     Nut&Honey_Crunch   K    C      120
2   1    190
50            Nutri-Grain_Almond-Raisin   K    C      140
3   2    220
51                    Nutri-grain_Wheat   K    C       90
3   0    170
52                 Oatmeal_Raisin_Crisp   G    C      130
3   2    170
53               Post_Nat._Raisin_Bran   P    C      120
3   1    200
54                           Product_19   K    C      100
3   0    320
55                          Puffed_Rice   Q    C       50
1   0      0
56                         Puffed_Wheat   Q    C       50
2   0      0
57                   Quaker_Oat_Squares   Q    C      100
4   1    135
58                       Quaker_Oatmeal   Q    H      100
5   2      0
59                          Raisin_Bran   K    C      120
3   1    210
60                      Raisin_Nut_Bran   G    C      100
3   2    140
61                       Raisin_Squares   K    C       90
2   0      0
62                            Rice_Chex   R    C      110
1   0    240
63                        Rice_Krispies   K    C      110
2   0    290
64                       Shredded_Wheat   N    C       80
2   0      0
65              Shredded_Wheat_'n'Bran   N    C       90
```

```
3   0      0
66             Shredded_Wheat_spoon_size   N    C       90
3   0      0
67                                Smacks   K    C      110
2   1     70
68                             Special_K   K    C      110
6   0    230
69               Strawberry_Fruit_Wheats   N    C       90
2   0     15
70                      Total_Corn_Flakes   G    C      110
2   1    200
71                      Total_Raisin_Bran   G    C      140
3   1    190
72                      Total_Whole_Grain   G    C      100
3   1    200
73                               Triples   G    C      110
2   1    250
74                                  Trix   G    C      110
1   1    140
75                            Wheat_Chex   R    C      100
3   1    230
76                              Wheaties   G    C      100
3   1    200
77                    Wheaties_Honey_Gold   G    C      110
2   1    200
   fiber carbo sugars potass vitamins shelf weight cups
rating
1   10.0   5.0      6    280       25     3   1.00 0.33
68.40297
2    2.0   8.0      8    135        0     3   1.00 1.00
33.98368
3    9.0   7.0      5    320       25     3   1.00 0.33
59.42551
4   14.0   8.0      0    330       25     3   1.00 0.50
93.70491
5    1.0  14.0      8     -1       25     3   1.00 0.75
34.38484
6    1.5  10.5     10     70       25     1   1.00 0.75
29.50954
7    1.0  11.0     14     30       25     2   1.00 1.00
33.17409
8    2.0  18.0      8    100       25     3   1.33 0.75
37.03856
9    4.0  15.0      6    125       25     1   1.00 0.67
49.12025
10   5.0  13.0      5    190       25     3   1.00 0.67
53.31381
11   0.0  12.0     12     35       25     2   1.00 0.75
```

```
18.04285
12   2.0  17.0      1    105       25     1   1.00 1.25
50.76500
13   0.0  13.0      9     45       25     2   1.00 0.75
19.82357
14   2.0  13.0      7    105       25     3   1.00 0.50
40.40021
15   0.0  12.0     13     55       25     2   1.00 1.00
22.73645
16   0.0  22.0      3     25       25     1   1.00 1.00
41.44502
17   1.0  21.0      2     35       25     1   1.00 1.00
45.86332
18   1.0  13.0     12     20       25     2   1.00 1.00
35.78279
19   0.0  12.0     13     65       25     2   1.00 1.00
22.39651
20   4.0  10.0      7    160       25     3   1.00 0.50
40.44877
21   1.0  21.0      0     -1        0     2   1.00 1.00
64.53382
22   1.0  21.0      3     30       25     3   1.00 1.00
46.89564
23   2.0  11.0     10    120       25     3   1.00 0.75
36.17620
24   1.0  18.0      5     80       25     3   1.00 0.75
44.33086
25   1.0  11.0     13     30       25     2   1.00 1.00
32.20758
26   1.0  14.0     11     25       25     1   1.00 0.75
31.43597
27   3.0  14.0      7    100       25     2   1.00 0.80
58.34514
28   5.0  12.0     10    200       25     3   1.25 0.67
40.91705
29   5.0  14.0     12    190       25     3   1.33 0.67
41.01549
30   0.0  13.0     12     25       25     2   1.00 0.75
28.02576
31   0.0  11.0     15     40       25     1   1.00 0.88
35.25244
32   0.0  15.0      9     45       25     2   1.00 0.75
23.80404
33   3.0  15.0      5     85       25     3   1.00 0.88
52.07690
34   3.0  17.0      3     90       25     3   1.00 0.25
53.37101
35   3.0  13.0      4    100       25     3   1.00 0.33
```

```
45.81172
36   1.0  12.0     11     45       25     2   1.00 1.00
21.87129
37   1.5  11.5     10     90       25     1   1.00 0.75
31.07222
38   0.0  14.0     11     35       25     1   1.00 1.33
28.74241
39   1.0  17.0      6     60      100     3   1.00 1.00
36.52368
40   2.0  20.0      9     95      100     3   1.30 0.75
36.47151
41   0.0  21.0      3     40       25     2   1.00 1.50
39.24111
42   2.0  12.0      6     95       25     2   1.00 0.67
45.32807
43   0.0  12.0     12     55       25     2   1.00 1.00
26.73451
44   0.0  16.0      3     95       25     2   1.00 1.00
54.85092
45   3.0  16.0     11    170       25     3   1.00 1.00
37.13686
46   3.0  16.0     11    170       25     3   1.00 1.00
34.13976
47   3.0  17.0     13    160       25     3   1.50 0.67
30.31335
48   2.0  15.0      6     90       25     1   1.00 1.00
40.10596
49   0.0  15.0      9     40       25     2   1.00 0.67
29.92429
50   3.0  21.0      7    130       25     3   1.33 0.67
40.69232
51   3.0  18.0      2     90       25     3   1.00 1.00
59.64284
52   1.5  13.5     10    120       25     3   1.25 0.50
30.45084
53   6.0  11.0     14    260       25     3   1.33 0.67
37.84059
54   1.0  20.0      3     45      100     3   1.00 1.00
41.50354
55   0.0  13.0      0     15        0     3   0.50 1.00
60.75611
56   1.0  10.0      0     50        0     3   0.50 1.00
63.00565
57   2.0  14.0      6    110       25     3   1.00 0.50
49.51187
58   2.7  -1.0     -1    110        0     1   1.00 0.67
50.82839
59   5.0  14.0     12    240       25     2   1.33 0.75
```

```
39.25920
60   2.5  10.5      8    140        25      3    1.00 0.50
39.70340
61   2.0  15.0      6    110        25      3    1.00 0.50
55.33314
62   0.0  23.0      2     30        25      1    1.00 1.13
41.99893
63   0.0  22.0      3     35        25      1    1.00 1.00
40.56016
64   3.0  16.0      0     95         0      1    0.83 1.00
68.23588
65   4.0  19.0      0    140         0      1    1.00 0.67
74.47295
66   3.0  20.0      0    120         0      1    1.00 0.67
72.80179
67   1.0   9.0     15     40        25      2    1.00 0.75
31.23005
68   1.0  16.0      3     55        25      1    1.00 1.00
53.13132
69   3.0  15.0      5     90        25      2    1.00 1.00
59.36399
70   0.0  21.0      3     35       100      3    1.00 1.00
38.83975
71   4.0  15.0     14    230       100      3    1.50 1.00
28.59278
72   3.0  16.0      3    110       100      3    1.00 1.00
46.65884
73   0.0  21.0      3     60        25      3    1.00 0.75
39.10617
74   0.0  13.0     12     25        25      2    1.00 1.00
27.75330
75   3.0  17.0      3    115        25      1    1.00 0.67
49.78744
76   3.0  17.0      3    110        25      1    1.00 1.00
51.59219
77   1.0  16.0      8     60        25      1    1.00 0.75
36.18756
```

▼ Code

```
levels(cereal.with.factors$mfr)
```

```
[1] "A" "G" "K" "N" "P" "Q" "R"
```

▼ Code

```
class(cereal.with.factors$mfr)
```

```
[1] "factor"
```

▼ Code

```
class(cereal$mfr)
```

```
[1] "character"
```

▼ Code

```
# or
class(cereal.with.factors$carbo)
```

```
[1] "numeric"
```

▼ Code

```
class(cereal$carbo)
```

```
[1] "numeric"
```

▼ Code

```
# or
str(cereal.with.factors) #only characters become factors
```

```
'data.frame':	77 obs. of  16 variables:
 $ name    : Factor w/ 77 levels
"100%_Bran","100%_Natural_Bran",..: 1 2 3 4 5 6 7 8 9 10 ...
 $ mfr     : Factor w/ 7 levels "A","G","K","N",..: 4 6 3 3 7
2 3 2 7 5 ...
 $ type    : Factor w/ 2 levels "C","H": 1 1 1 1 1 1 1 1 1 1
...
 $ calories: int  70 120 70 50 110 110 110 130 90 90 ...
 $ protein : int  4 3 4 4 2 2 2 3 2 3 ...
 $ fat     : int  1 5 1 0 2 2 0 2 1 0 ...
 $ sodium  : int  130 15 260 140 200 180 125 210 200 210 ...
 $ fiber   : num  10 2 9 14 1 1.5 1 2 4 5 ...
 $ carbo   : num  5 8 7 8 14 10.5 11 18 15 13 ...
 $ sugars  : int  6 8 5 0 8 10 14 8 6 5 ...
 $ potass  : int  280 135 320 330 -1 70 30 100 125 190 ...
 $ vitamins: int  25 0 25 25 25 25 25 25 25 25 ...
 $ shelf   : int  3 3 3 3 3 1 2 3 1 3 ...
 $ weight  : num  1 1 1 1 1 1 1 1.33 1 1 ...
 $ cups    : num  0.33 1 0.33 0.5 0.75 0.75 1 0.75 0.67 0.67
...
```

```
 $ rating  : num  68.4 34 59.4 93.7 34.4 ...
```

▼ Code

```
str(cereal)
```

```
spc_tbl_ [77 × 16] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
 $ name    : chr [1:77] "100%_Bran" "100%_Natural_Bran" "All-
Bran" "All-Bran_with_Extra_Fiber" ...
 $ mfr     : chr [1:77] "N" "Q" "K" "K" ...
 $ type    : chr [1:77] "C" "C" "C" "C" ...
 $ calories: num [1:77] 70 120 70 50 110 110 110 130 90 90 ...
 $ protein : num [1:77] 4 3 4 4 2 2 2 3 2 3 ...
 $ fat     : num [1:77] 1 5 1 0 2 2 0 2 1 0 ...
 $ sodium  : num [1:77] 130 15 260 140 200 180 125 210 200 210
...
 $ fiber   : num [1:77] 10 2 9 14 1 1.5 1 2 4 5 ...
 $ carbo   : num [1:77] 5 8 7 8 14 10.5 11 18 15 13 ...
 $ sugars  : num [1:77] 6 8 5 0 8 10 14 8 6 5 ...
 $ potass  : num [1:77] 280 135 320 330 -1 70 30 100 125 190
...
 $ vitamins: num [1:77] 25 0 25 25 25 25 25 25 25 25 ...
 $ shelf   : num [1:77] 3 3 3 3 3 1 2 3 1 3 ...
 $ weight  : num [1:77] 1 1 1 1 1 1 1 1.33 1 1 ...
 $ cups    : num [1:77] 0.33 1 0.33 0.5 0.75 0.75 1 0.75 0.67
0.67 ...
 $ rating  : num [1:77] 68.4 34 59.4 93.7 34.4 ...
 - attr(*, "spec")=
  .. cols(
  ..   name = col_character(),
  ..   mfr = col_character(),
  ..   type = col_character(),
  ..   calories = col_double(),
  ..   protein = col_double(),
  ..   fat = col_double(),
  ..   sodium = col_double(),
  ..   fiber = col_double(),
  ..   carbo = col_double(),
  ..   sugars = col_double(),
  ..   potass = col_double(),
  ..   vitamins = col_double(),
  ..   shelf = col_double(),
  ..   weight = col_double(),
  ..   cups = col_double(),
  ..   rating = col_double()
  .. )
 - attr(*, "problems")=<externalptr>
```

b. How many levels are there in `mfr` and `type`? (use the functions `levels` or `nlevels`)

Solution

▼ Code

```
levels(cereal.with.factors$mfr)
```

```
[1] "A" "G" "K" "N" "P" "Q" "R"
```

▼ Code

```
# or
nlevels(cereal.with.factors$mfr)
```

```
[1] 7
```

▼ Code

```
# or
str(cereal.with.factors$mfr)
```

```
 Factor w/ 7 levels "A","G","K","N",..: 4 6 3 3 7 2 3 2 7 5
...
```

▼ Code

```
# class() typeof()
```

Vectors

a. Extract the `calories` into a new vector called `cereal.calories`.

Solution

▼ Code

```
cereal.calories <- cereal$calories
cereal.calories <- cereal[["calories"]]
cereal_calories <- cereal_tbl %>% pull(calories)
```

b. How many elements are there in `cereal.calories`? (`length`)

Solution

▼ Code

```
length(cereal.calories)
```

```
[1] 77
```

▼ Code

```
cereal_calories %>% length()
```

```
[1] 77
```

c. Extract the 5th to the 10th element from `cereal.calories`.

Solution

▼ Code

```
# cereal.calories[5:10] # most code works this way
cereal_calories[5:10]
```

```
[1] 110 110 110 130  90  90
```

d. Add one more element to `cereal.calories` using `c()`.

Solution

▼ Code

```
cereal_calories <- c(cereal_calories, 1.0) #c for concater
length(cereal.calories)
```

```
[1] 77
```

Matrix

a. Can you force the cereal data frame to be a Matrix? (`as.matrix(cereal)`). Check that the elements have been forced into the character type.

Solution

▼ Code

```
cereal.matrix <- as.matrix(cereal)
str(cereal.matrix)
```

```
 chr [1:77, 1:16] "100%_Bran" "100%_Natural_Bran" "All-Bran"
...
 - attr(*, "dimnames")=List of 2
  ..$ : NULL
  ..$ : chr [1:16] "name" "mfr" "type" "calories" ...
```

b. Now do this again, but this time leave out the `mfr`, `name` and `type` columns. Check that the elements are now numeric.

Solution

▼ Code

```
cereal.removed <- cereal[, -(1:3)]
cereal.removed
```

```
# A tibble: 77 × 13
   calories protein   fat sodium fiber carbo sugars potass
vitamins shelf weight
      <dbl>   <dbl> <dbl>  <dbl> <dbl> <dbl>  <dbl>  <dbl>
<dbl> <dbl>  <dbl>
 1       70       4     1    130  10      5       6    280
25     3   1
 2      120       3     5     15   2      8       8    135
0     3   1
 3       70       4     1    260   9      7       5    320
25     3   1
 4       50       4     0    140  14      8       0    330
25     3   1
 5      110       2     2    200   1     14       8     -1
25     3   1
 6      110       2     2    180   1.5  10.5     10     70
25     1   1
 7      110       2     0    125   1     11      14     30
25     2   1
 8      130       3     2    210   2     18       8    100
25     3   1.33
 9       90       2     1    200   4     15       6    125
25     1   1
10       90       3     0    210   5     13       5    190
25     3   1
# … with 67 more rows, and 2 more variables: cups <dbl>,
rating <dbl>
```

▼ Code

```
cereal.numeric.matrix <- as.matrix(cereal.removed)
str(cereal.numeric.matrix)
```

```
num [1:77, 1:13] 70 120 70 50 110 110 110 130 90 90 ...
- attr(*, "dimnames")=List of 2
 ..$ : NULL
 ..$ : chr [1:13] "calories" "protein" "fat" "sodium" ...
```

1.3 Numerical summary

Summary

a. Use the `summary` function to extract the median, 1st quartile and 3rd quartile data from the `sodium` column.

Solution

▼ Code

```
summary(cereal$sodium)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
    0.0   130.0   180.0   159.7   210.0   320.0 
```

Basic statistics

b. Find the max, min, standard deviation and mean of the `sodium` (`max()`, `min()`, `sd()`, `mean()`)

Solution

▼ Code

```
cereal_tbl %>% pull(sodium) %>% summary()
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
    0.0   130.0   180.0   159.7   210.0   320.0 
```

▼ Code

```
sodium<-cereal$sodium
max(sodium)
```

```
[1] 320
```

▼ Code

```
min(cereal$sodium)
```

```
[1] 0
```

▼ Code

```
sd(cereal$sodium)
```

```
[1] 83.8323
```

▼ Code

```
mean(cereal$sodium)
```

```
[1] 159.6753
```

▼ Code

```
summary(sodium)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
    0.0   130.0   180.0   159.7   210.0   320.0 
```

c. Find the mean `sodium` of each `mfr`.

Solution

▼ Code

```
### Can be done by repeated subsetting, this is tedious
kelloggs.cereals <- subset(cereal, mfr == "K")
mean(kelloggs.cereals$sodium)
```

```
[1] 174.7826
```

▼ Code

```
### Can use a formula and the aggregate function

mean.sodiums <- aggregate(sodium ~ mfr, data = cereal, FUN
### Can split vector (or data.frame if you wanted) by
### another vector. In this case, split by species.
```

```
split.sodium <- split(cereal$sodium, cereal$mfr)
### Apply a function over a list and return a list (_l_app
lapply(split.sodium, mean)
```

```
$A
[1] 0

$G
[1] 200.4545

$K
[1] 174.7826

$N
[1] 37.5

$P
[1] 146.1111

$Q
[1] 92.5

$R
[1] 198.125
```

▼ Code

```
### Apply a function over a list and return a _s_implified
sapply(split.sodium, mean)
```

```
       A        G        K        N        P        Q        R 
  0.0000 200.4545 174.7826  37.5000 146.1111  92.5000 198.1250 
```

▼ Code

```
### Also could use by and tapply, vapply, for the interest

cereal_tbl %>%
    select(sodium, mfr) %>%
    group_by(mfr) %>%
    summarise(mean_sodium = mean(sodium))
```

```
# A tibble: 7 × 2
  mfr   mean_sodium
  <chr>       <dbl>
1 A             0  
2 G           200. 
```

```
3 K             175.
4 N              37.5
5 P             146.
6 Q              92.5
7 R             198.
```

1.4 Graphical summary

Boxplot

a. Make a boxplot of the `sodium` against `mfr` using `boxplot()`.

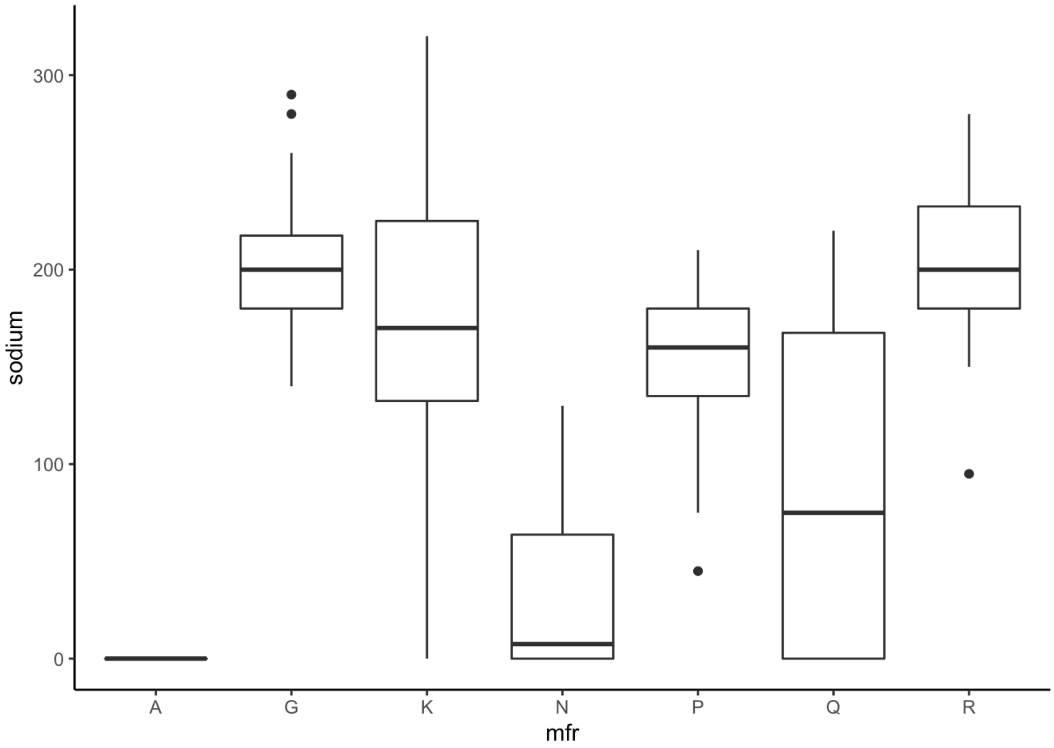
Solution

▼ Code

```
boxplot(sodium ~ mfr, data = cereal,
        xlab = "Manufacturer", ylab = "Sodium content", ma
```

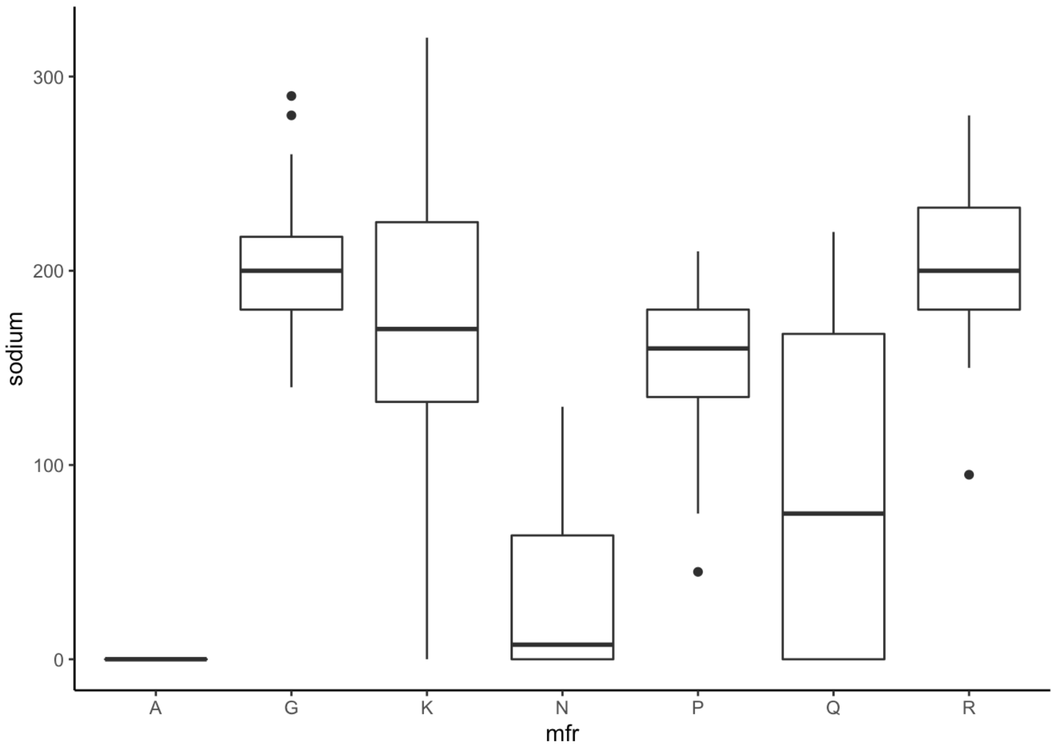
▼ Code

```
ggplot(cereal_tbl, aes(x = mfr, y = sodium)) + geom_boxplc
```



▼ Code

```
cereal_tbl %>% ggplot(aes(x = mfr, y = sodium)) + geom_box
```



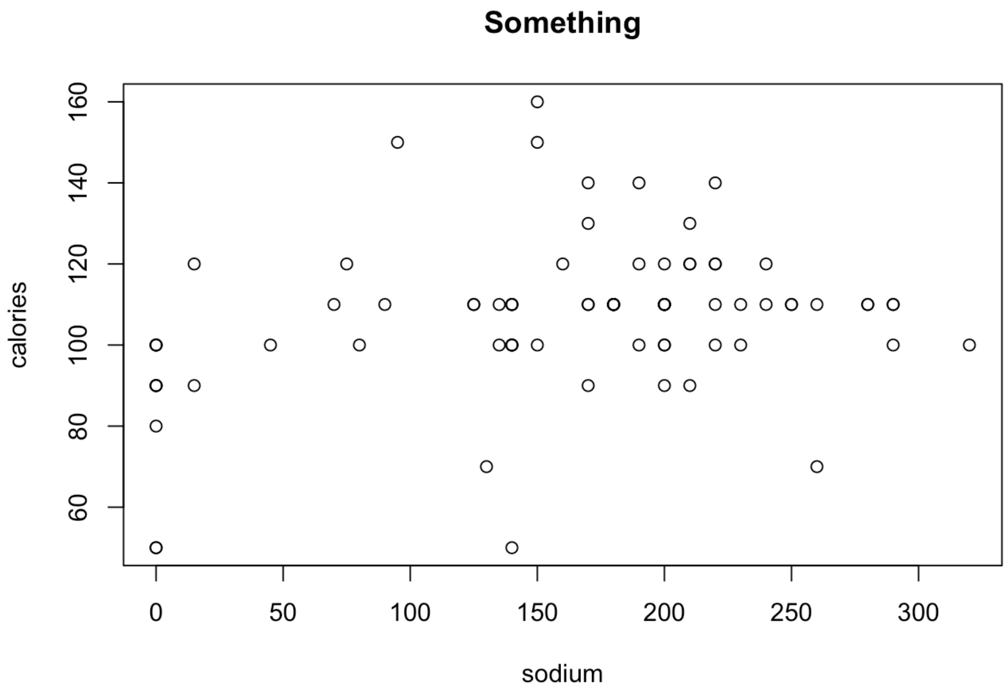
Scatterplot

b. Plot `calories` against `sodium` using `plot()`.

Solution

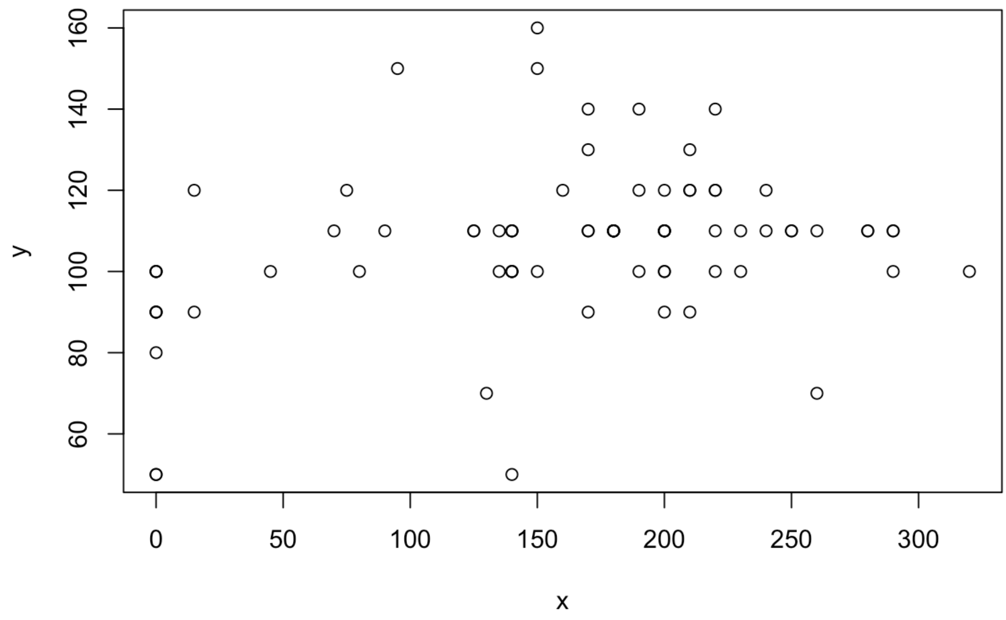
▼ Code

```r
### Using formula
plot(calories ~ sodium, data = cereal, main = "Something")
```



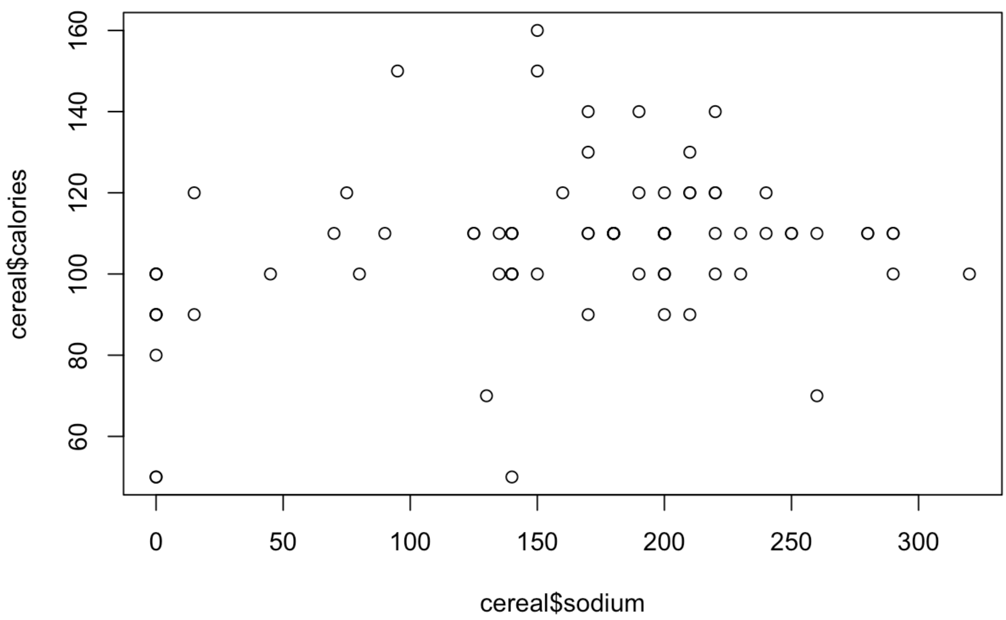
▼ Code

```r
### Another way, define x and y
x <- cereal$sodium
y <- cereal$calories
plot(x, y)
```



▼ Code

```
plot(cereal$sodium, cereal$calories)
```

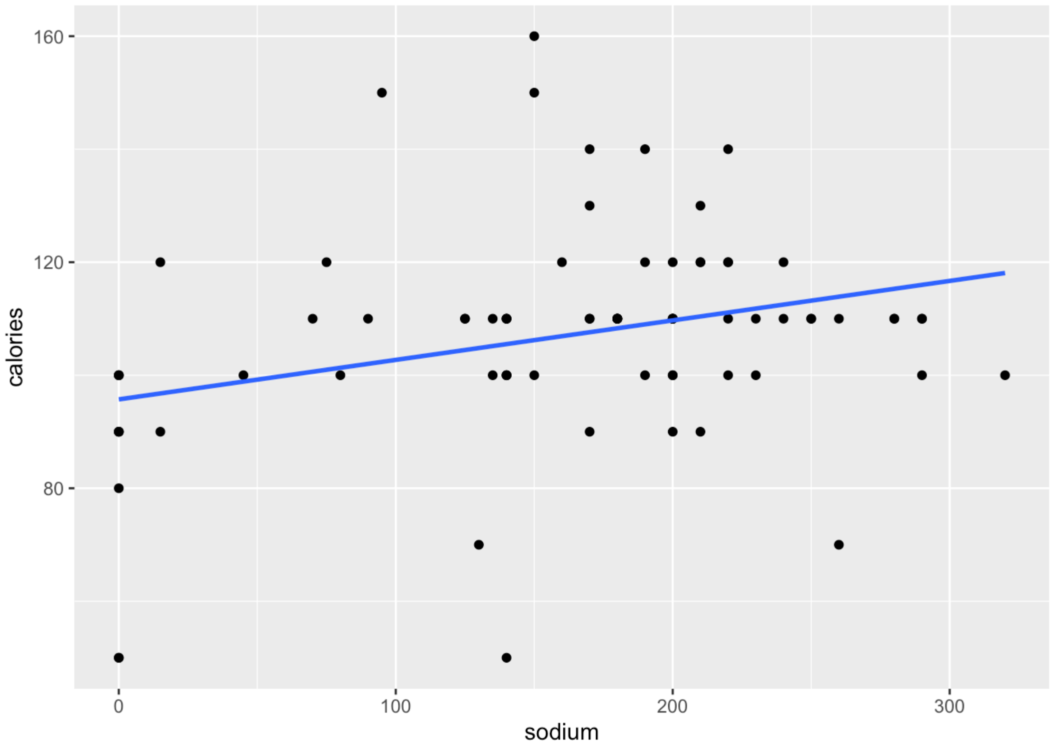


▼ Code

```
### Alternatively, use with to help R find the vectors
###with(cereal, plot(sodium, calories))
```

```
ggplot(cereal_tbl, aes(x = sodium, y = calories)) +
    geom_point() + geom_smooth(method = "lm", se = FALSE)
```

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



1.5 Write Data to File

b. Write data frame with only the Kellogg's observations to a file called `kelloggs.csv`. Use the `write.csv` command.

Solution

▼ Code

```
write.csv(kelloggs_tbl, file = "kelloggs.csv")
head(cereal)
```

```
# A tibble: 6 × 16
  name         mfr   type  calor…¹ protein   fat sodium fiber
carbo sugars potass
  <chr>        <chr> <chr>   <dbl>   <dbl> <dbl>  <dbl> <dbl>
<dbl>  <dbl>  <dbl>
1 100%_Bran    N     C          70       4     1    130   10
5        6    280
2 100%_Natur… Q     C         120       3     5     15    2
8        8    135
```

```
3 All−Bran     K      C           70        4      1     260    9
7         5     320
4 All−Bran_w… K      C           50        4      0     140   14
8         0     330
5 Almond_Del… R      C          110        2      2     200    1
14         8      −1
6 Apple_Cinn… G      C          110        2      2     180    1.5
10.5      10      70
# … with 5 more variables: vitamins <dbl>, shelf <dbl>, weight
<dbl>,
#   cups <dbl>, rating <dbl>, and abbreviated variable name ¹
calories
```

2 Melbourne house prices regression model

In this section we will examine the dataset describing Melbourne house prices. This dataset was downloaded from Kaggle and the data was released under the CC BY-NC-SA 4.0 license. For this lab, we will focus on three subrubs - Brunswick, Craigieburn and Hawthorn and examine what variables or factors are associated with the housing price.

2.1 Load the data

Load the Melbourne house price dataset from Canvas.

Solution

▼ Code

```
melb.dat <- read.csv("Melbourne_housing_FULL.csv")
melbdata <- read_csv("Melbourne_housing_FULL.csv")
```

```
Rows: 34857 Columns: 21
── Column specification
────────────────────────────────────────────────────────
Delimiter: ","
chr  (8): Suburb, Address, Type, Method, SellerG, Date,
CouncilArea, Regionname
dbl (13): Rooms, Price, Distance, Postcode, Bedroom2,
Bathroom, Car, Landsiz...

ℹ Use `spec()` to retrieve the full column specification for
this data.
ℹ Specify the column types or set `show_col_types = FALSE` to
```

```
quiet this message.
```

2.2 Initial data analysis

We will need to subset the data to only look at 3 suburbs - Brunswick, Craigieburn and Hawthorn. Similar to lab 1, start the data analysis by generating some quantitative and graphical summaries. For example, determine the average price in each of these three suburbs. Explore more summaries of the data.

Solution

▼ Code

```
### Base R
melb.data.sub <- subset(melbdata, Suburb == "Hawthorn" | S
melb.data.sub2 <- subset(melbdata, Suburb %in% c("Hawthorn
identical(melb.data.sub, melb.data.sub2)
```

```
[1] TRUE
```

▼ Code

```
split.data <- split(melb.data.sub[["Price"]], melb.data.su
suburb.means <- vapply(split.data, mean, numeric(1L), na.r
suburb.medians <- vapply(split.data, median, numeric(1L),
```

▼ Code

```
### Tidyverse way
melbdata.sub <- melbdata %>%
    filter(Suburb %in% c("Hawthorn", "Brunswick", "Craigie
    mutate(Suburb = factor(Suburb, levels = c("Craigieburn

melbdata %>%
  filter(Suburb %in% c("Hawthorn", "Brunswick", "Craigiebu
  group_by(Suburb) %>%
  summarise(Mean_Price = mean(Price, na.rm = TRUE), Median
```

```
# A tibble: 3 × 3
  Suburb      Mean_Price Median_price
  <chr>            <dbl>        <dbl>
1 Brunswick      977989.       950000
2 Craigieburn    566173.       562500
3 Hawthorn      1238074.       750500
```

For the following questions, use the subsetted data for the Suburbs of Brunswick, Craigieburn and Hawthorn.

2.3 Finding association I

To examine the association between house prices and a single variable, start by constructing a simple linear regression using only `BuildingArea` as a predictor. Use an appropriate statistic to justify the goodness of fit of the prediction and create a graphical output to enable you to assess your model fit.

Note: you might consider other variables too.

Solution Consider a scatter plot of `Price` against `BuildingArea` and overlay the prediction from the linear regression model.

▼ Code

```
### FORM THE LINEAR REGRESSION MODEL
lm1 <- lm(data = melbdata.sub, Price/1000 ~ BuildingArea)

### Inspect coefficients
coef(lm1)
```

```
(Intercept) BuildingArea
 518.192115     3.800746
```

▼ Code

```
lm1 |> coef()#get coefficients
```

```
(Intercept) BuildingArea
 518.192115     3.800746
```

▼ Code

```
lm1 |> fitted() |> head() #fitted values
```

```
        2         3         4         9        11        12
 928.6727  871.6615 1312.5480 1609.0062  769.0413  670.2220
```

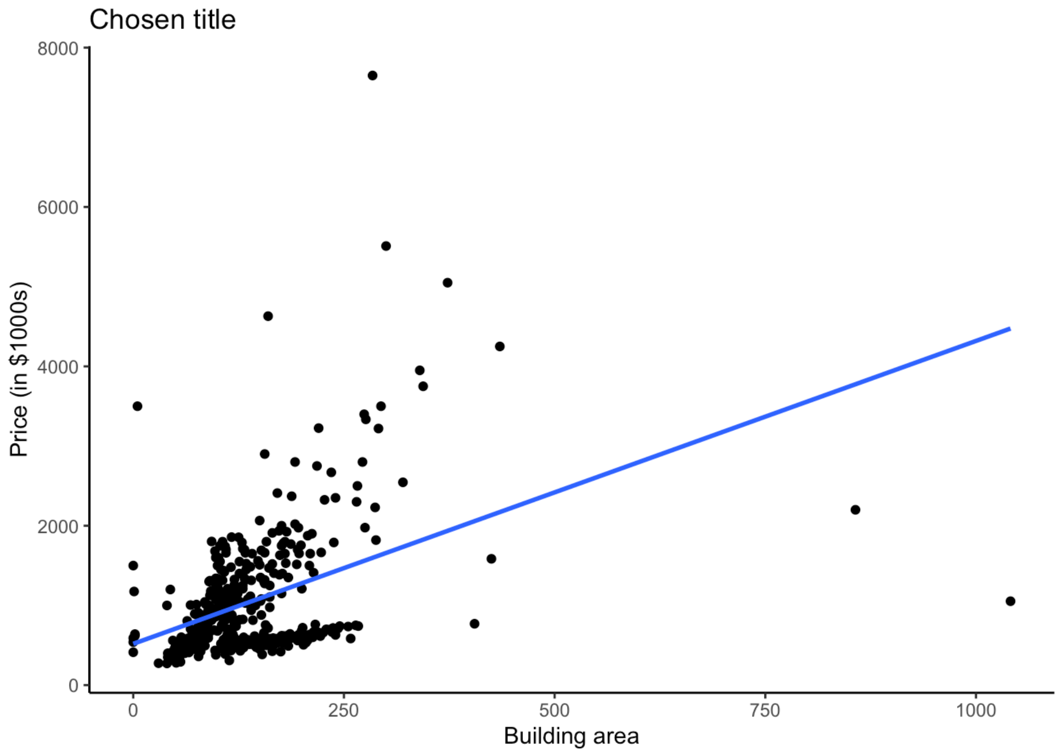
▼ Code

```
lm1 |> resid() |> head() #residuals ie errors, check mean
```

```
          2           3           4           9          11 
12 
  97.32732  930.83851  187.45198  620.99380 -359.04135 
-397.72195 
```

▼ Code

```
ggplot(melbdata.sub |> select(BuildingArea, Price) |> drop
    aes(x = BuildingArea, y = Price/1000) +
    geom_point() + geom_smooth(formula = y ~ x, method = '
    theme_classic() + labs(x = "Building area", y = "Price
```



▼ Code

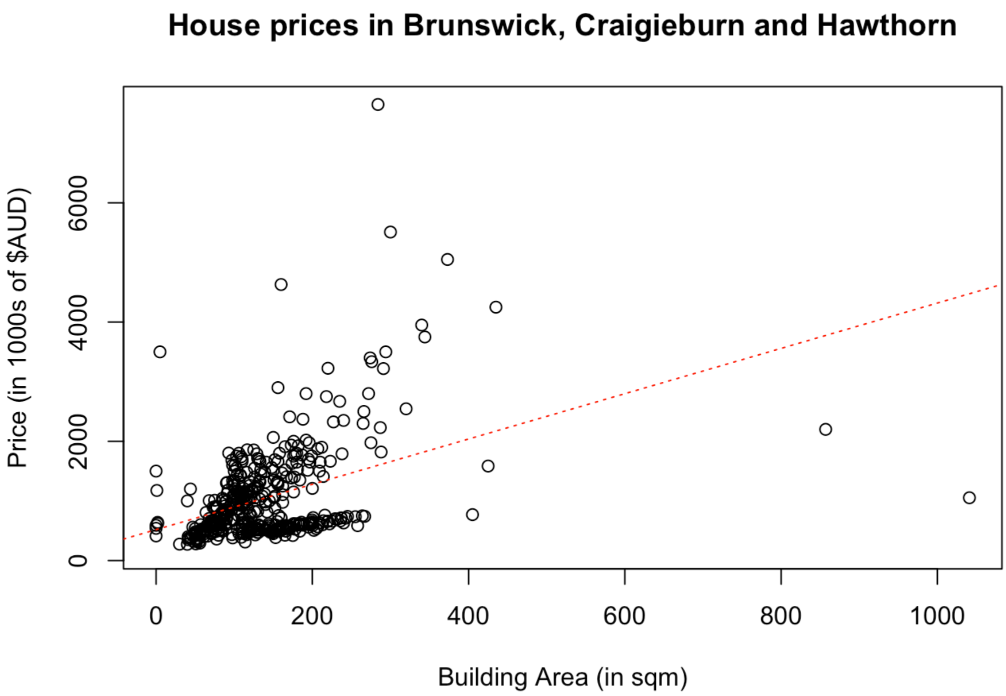
```
### Base R way
summary(lm1)
```

```
Call:
lm(formula = Price/1000 ~ BuildingArea, data = melbdata.sub)

Residuals:
    Min      1Q  Median      3Q     Max 
-3421.8  -463.9  -148.0   259.1  6052.4 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)  518.1921    66.5956   7.781 5.74e-14 ***
BuildingArea   3.8007     0.4082   9.311  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 730 on 416 degrees of freedom
  (709 observations deleted due to missingness)
Multiple R-squared:  0.1725,    Adjusted R-squared:  0.1705
F-statistic: 86.69 on 1 and 416 DF,  p-value: < 2.2e-16
```

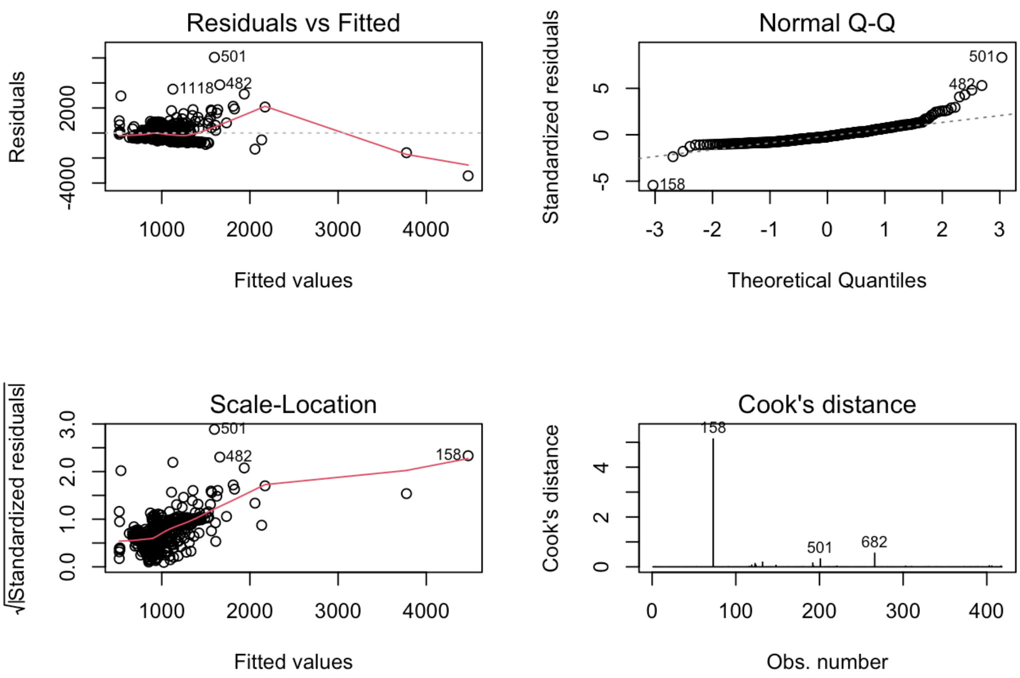
▼ Code

```
plot(Price/1000 ~ BuildingArea, data = melbdata.sub,
     main = "House prices in Brunswick, Craigieburn and Ha
     xlab = "Building Area (in sqm)", ylab = "Price (in 10
abline(lm1, col = "red", lty = "dotted")
```



▼ Code

```
par(mfrow = c(2, 2))
plot(lm1, which = 1:4)
```



▼ Code

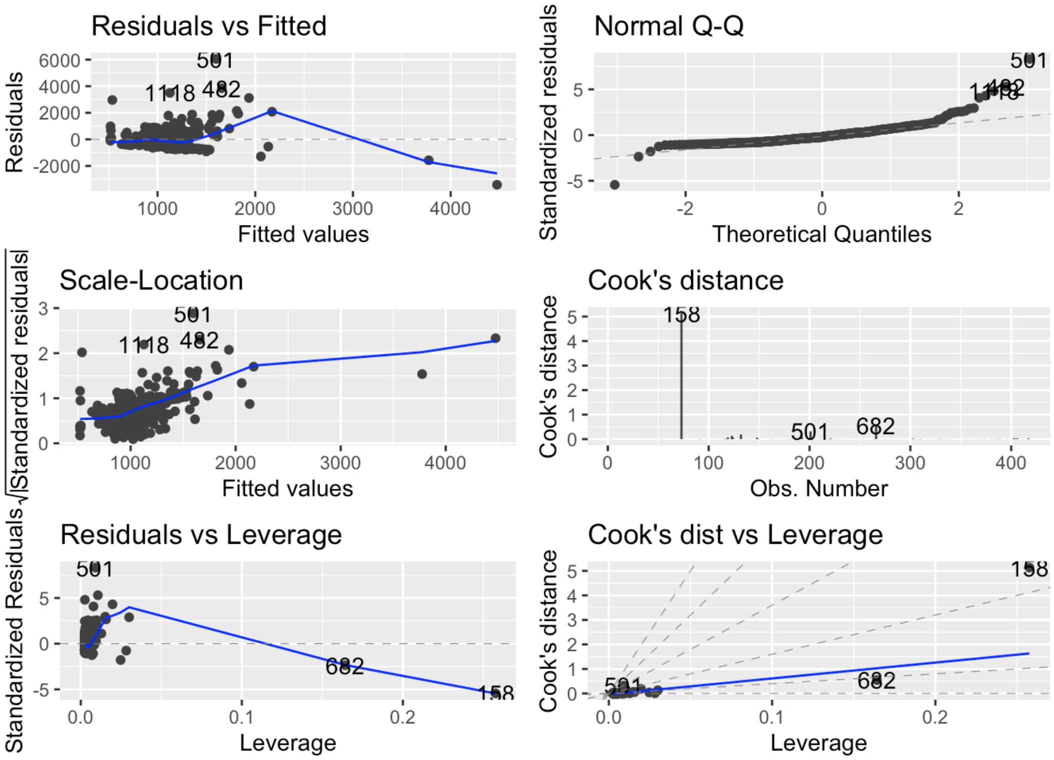
```
r2 <- round(summary(lm1)$r.squared, 4)
r2
```

```
[1] 0.1725
```

There is 17.25% of the variation in Price explained by the linear regression on Building Area.

▼ Code

```
### Tidyverse way
library(ggfortify)
autoplot(lm1, which = 1:6, nrow = 3, ncol = 2)
```



▼ Code

```
### LOTS OF NICE CONVENIENT CODE
### lm1 |> coefficients() #get coefficients
### lm1 |> fitted() #fitted values
### lm1 |> residuals() %>% mean()#residuals ie errors, che

library(broom)
lm1 |> augment() #full table of fitted values, cooks dista
```

```
# A tibble: 418 × 8
   .rownames `Price/1000` BuildingArea .fitted    .hat .sigma
.cooksd .std.…¹
   <chr>            <dbl>        <dbl>   <dbl>   <dbl>  <dbl>
<dbl>   <dbl>
 1 2                1026           108    929. 0.00267   731.
0.0000238   0.134
 2 3                1802.           93    872. 0.00302   729.
0.00247     1.28
 3 4                1500           209   1313. 0.00398   731.
0.000132    0.257
 4 9                2230           287   1609. 0.00936   730.
0.00345     0.855
 5 11                410            66    769. 0.00400   731.
0.000488   -0.493
 6 12                272.           40    670. 0.00538   731.
0.000807   -0.546
 7 13                680           100    898. 0.00284   731.
```

```
0.000128   -0.299
 8 16                400            61    750. 0.00423   731.
0.000491   -0.481
 9 17                950            96    883. 0.00294   731.
0.0000124   0.0918
10 20                860            97    887. 0.00291   731.
0.00000198 -0.0369
# … with 408 more rows, and abbreviated variable name ¹
.std.resid
```

▼ Code

```
lm1 |> glance() #key values eg R squared, can pull out
```

```
# A tibble: 1 × 12
  r.squared adj.r.squa…¹ sigma stati…²  p.value    df logLik
AIC   BIC devia…³
      <dbl>        <dbl> <dbl>   <dbl>    <dbl> <dbl>  <dbl>
<dbl> <dbl>   <dbl>
1     0.172        0.170  730.    86.7 7.41e-19     1 -3348.
6702. 6714.  2.22e8
# … with 2 more variables: df.residual <int>, nobs <int>, and
abbreviated
#   variable names ¹adj.r.squared, ²statistic, ³deviance
```

▼ Code

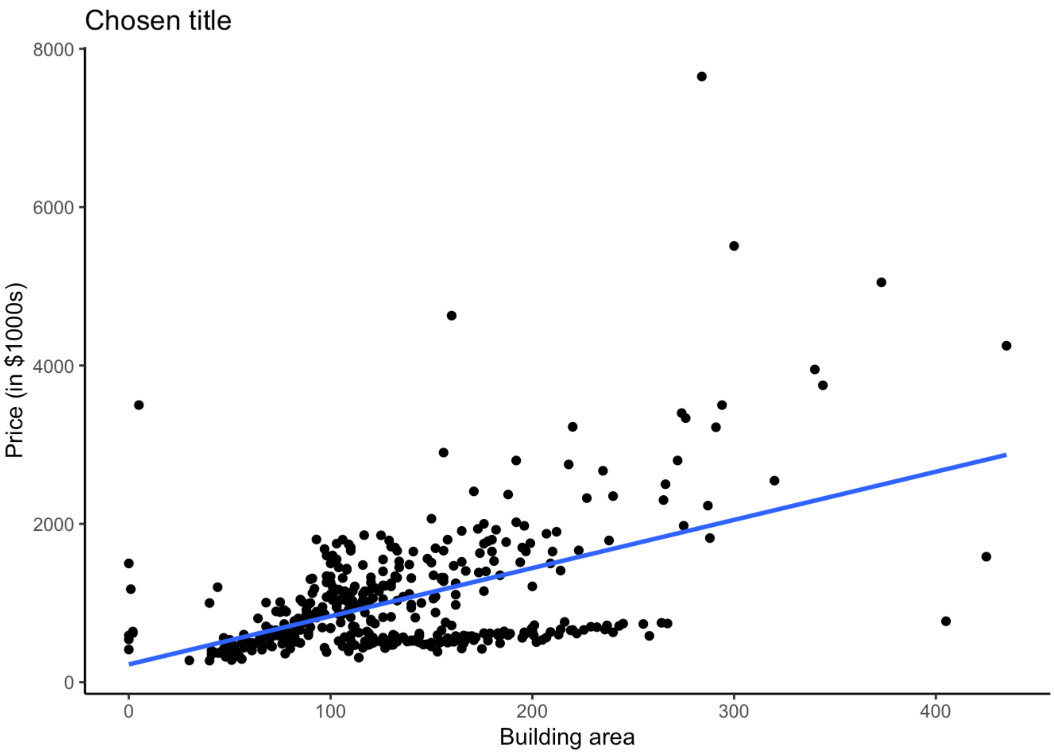
```
lm1 |> tidy() #conveniently puts summary into tibble forma
```

```
# A tibble: 2 × 5
  term         estimate std.error statistic  p.value
  <chr>           <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)    518.      66.6        7.78 5.74e-14
2 BuildingArea     3.80     0.408      9.31 7.41e-19
```

▼ Code

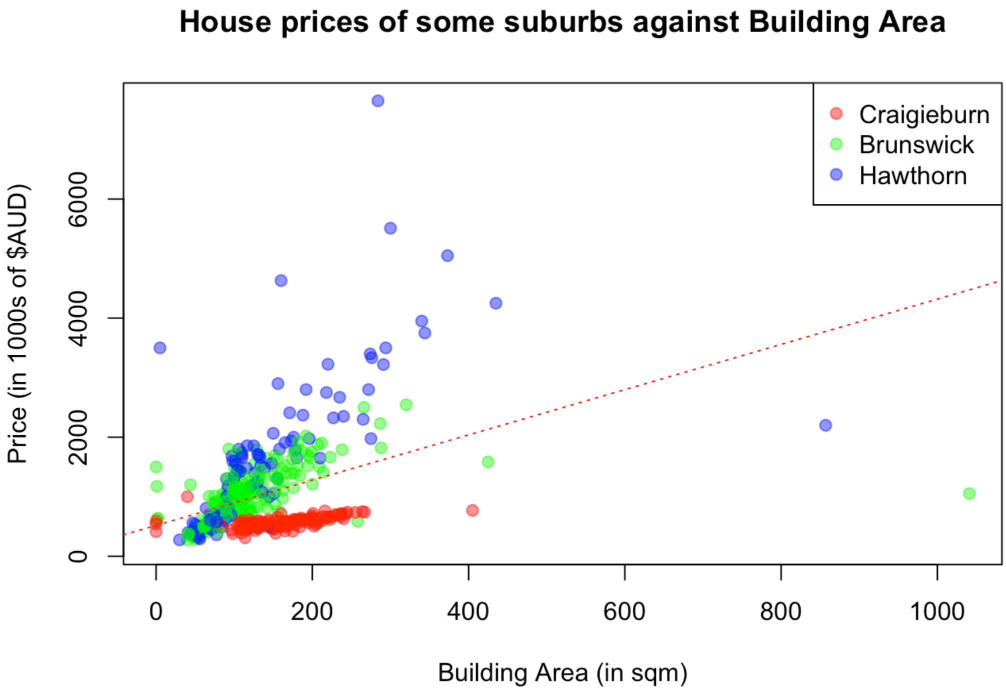
```
r2 <- lm1 |> glance() |> pull(r.squared)

melbdata.sub_out <- melbdata %>%
    filter(Suburb %in% c("Hawthorn", "Brunswick", "Craigie
    mutate(Suburb = factor(Suburb, levels = c("Craigieburn
    slice(-c(158,682)) #REMOVE THE WORST TWO OUTLIERS

lm1_alt <- lm(data = melbdata.sub_out, Price/1000 ~ Buildi

###OUTLIERS HAVE BEEN REMOVED
```

```
ggplot(melbdata.sub_out |> select(BuildingArea, Price) |>
    aes(x = BuildingArea, y = Price/1000) +
    geom_point() + geom_smooth(formula = y ~ x, method = '
    theme_classic() + labs(x = "Building area", y = "Price
```



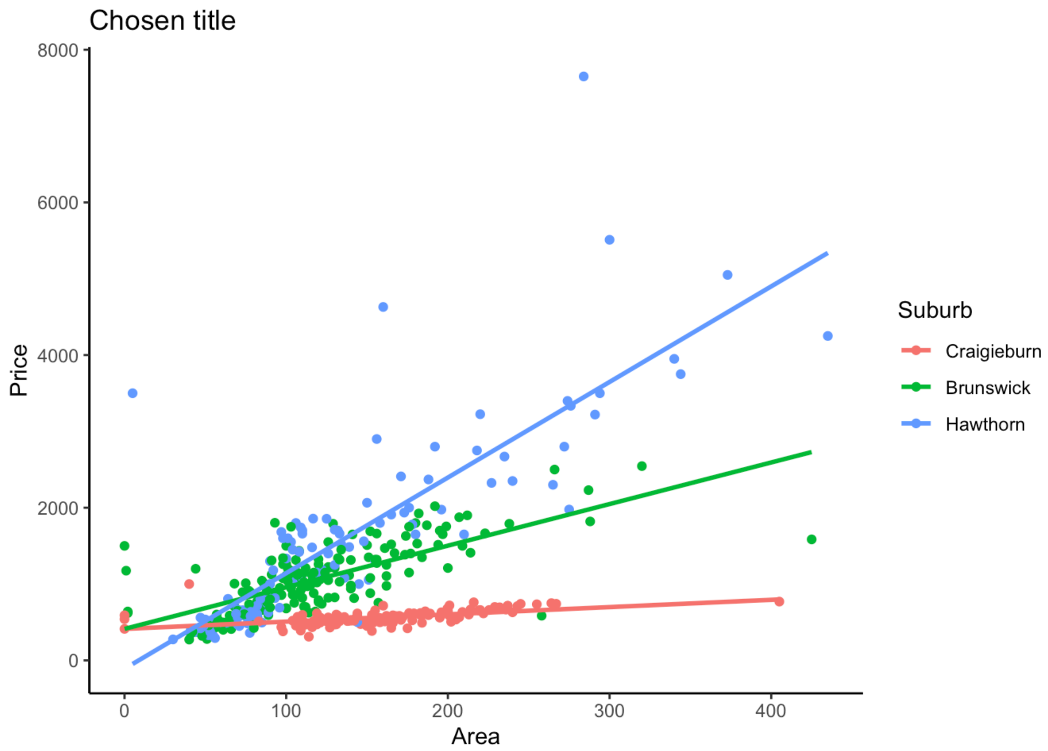
▼ Code

```
# Base R
lmfit1 <- lm(data = melbdata.sub, Price/1000 ~ BuildingAre
###Get semi-transparent red green and blue
my.colours <- rgb(c(1, 0, 0), c(0, 1, 0), c(0, 0, 1), alph
plot(Price/1000 ~ BuildingArea, data = melbdata.sub,
     main = "House prices of some suburbs against Building
     xlab = "Building Area (in sqm)", ylab = "Price (in 10
     col = my.colours[as.integer(melbdata.sub[["Suburb"]])
     pch = 19)
legend("topright", legend = levels(melbdata.sub[["Suburb"]
       col = my.colours, pch = 19)
abline(lmfit1, col = "red", lty = "dotted")
```



▼ Code

```
ggplot(melbdata.sub_out |> select(BuildingArea, Price, Sub
    aes(x = BuildingArea, y = Price/1000, color = Suburb)
    geom_point() +
    theme_classic() +
    labs(x = "Area", y = "Price", title = "Chosen title")
    geom_smooth(formula = y ~ x, method = "lm", se = FALSE
```



2.4 Finding association II

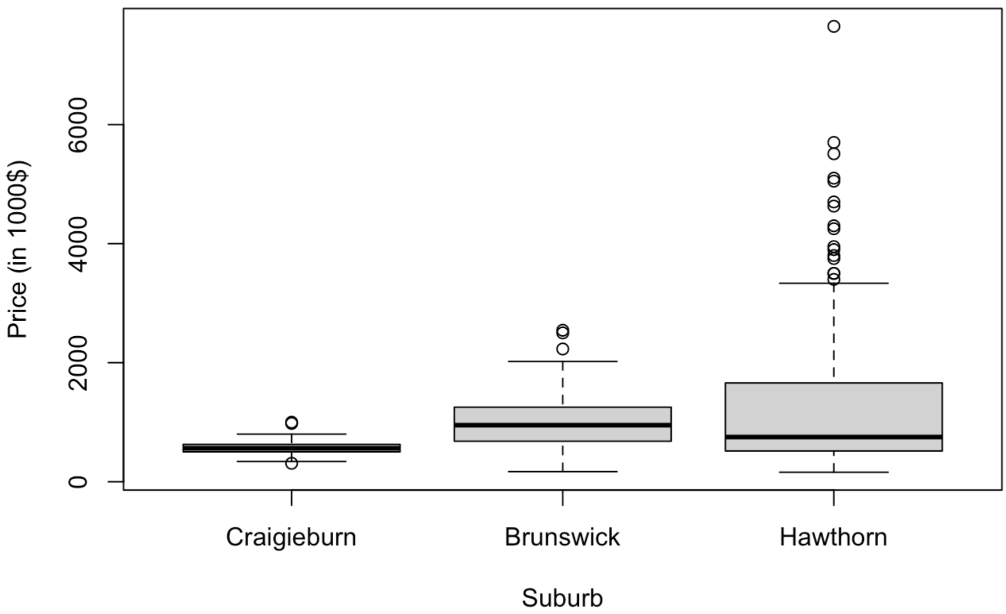
a. Variability of house prices are complex and likely to be explained by many different factors. Construct a multiple linear regression here by examining if adding `Suburb` as a predictor will improve the prediction? Notice that `Suburb` is a categorical variable. Briefly describe how to interpret the regression coefficients returned by `lm`.
b. There are many other variables in the data, you might consider whether adding the number of car spaces as a predictor improve the prediction model?

Solution

a. Model fit below

▼ Code

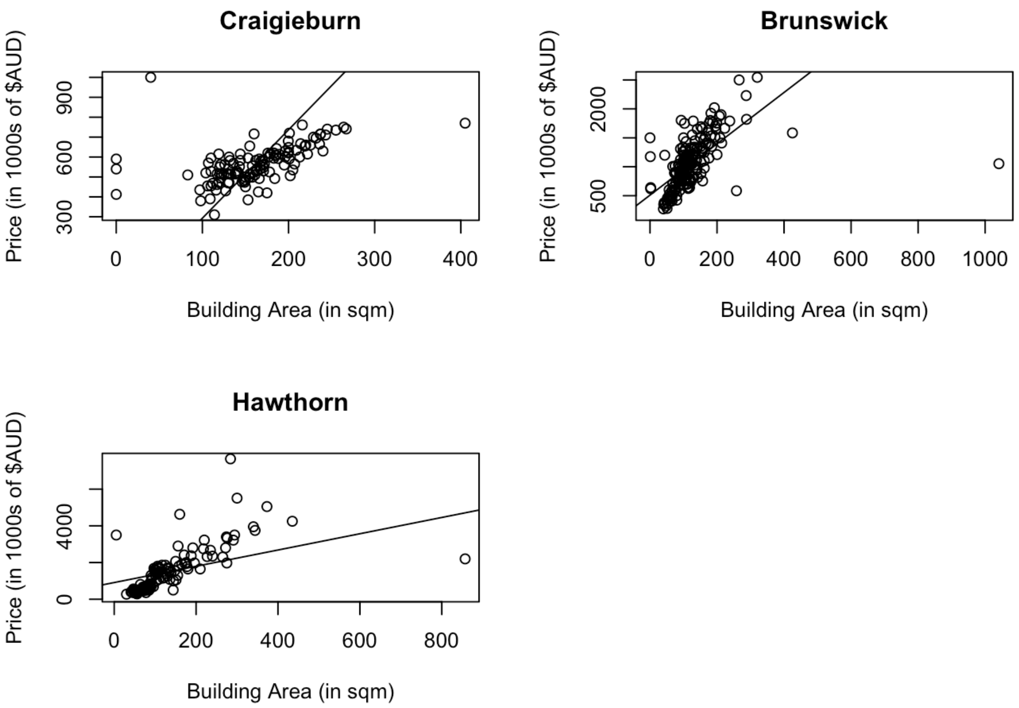
```
# Base R
boxplot(Price/1000 ~ Suburb, data = melbdata.sub, ylab = '
```



▼ Code

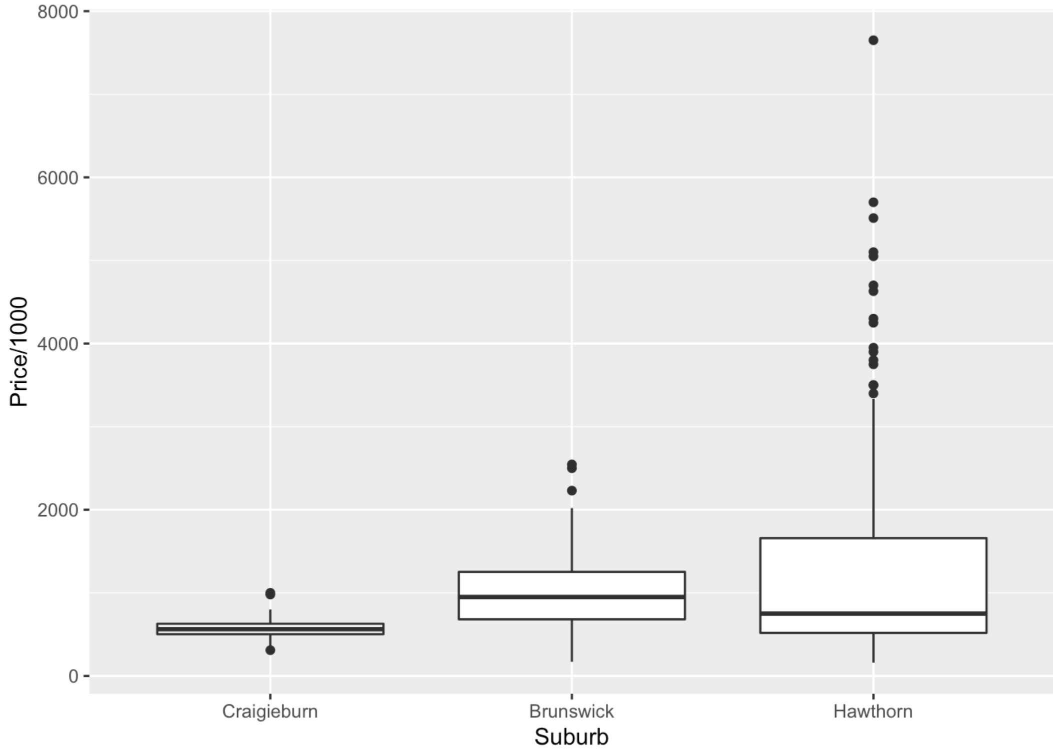
```
lm2 <- lm(Price/1000 ~ BuildingArea + Suburb, data = melb.
coefs <- lm2 |> coef()
```

```
# Base R
par(mfrow = c(2, 2))
invisible(lapply(levels(melbdata.sub$Suburb), function(x)
    plot(Price/1000 ~ BuildingArea, data = subset(melbdata
         xlab = "Building Area (in sqm)", ylab = "Price (i
    int <- coefs[1]
    if (any(adjust.ind <- grepl(paste0(x, "$"), names(coef
        int <- int + coefs[adjust.ind]
    abline(int, coefs[2])
}))
```



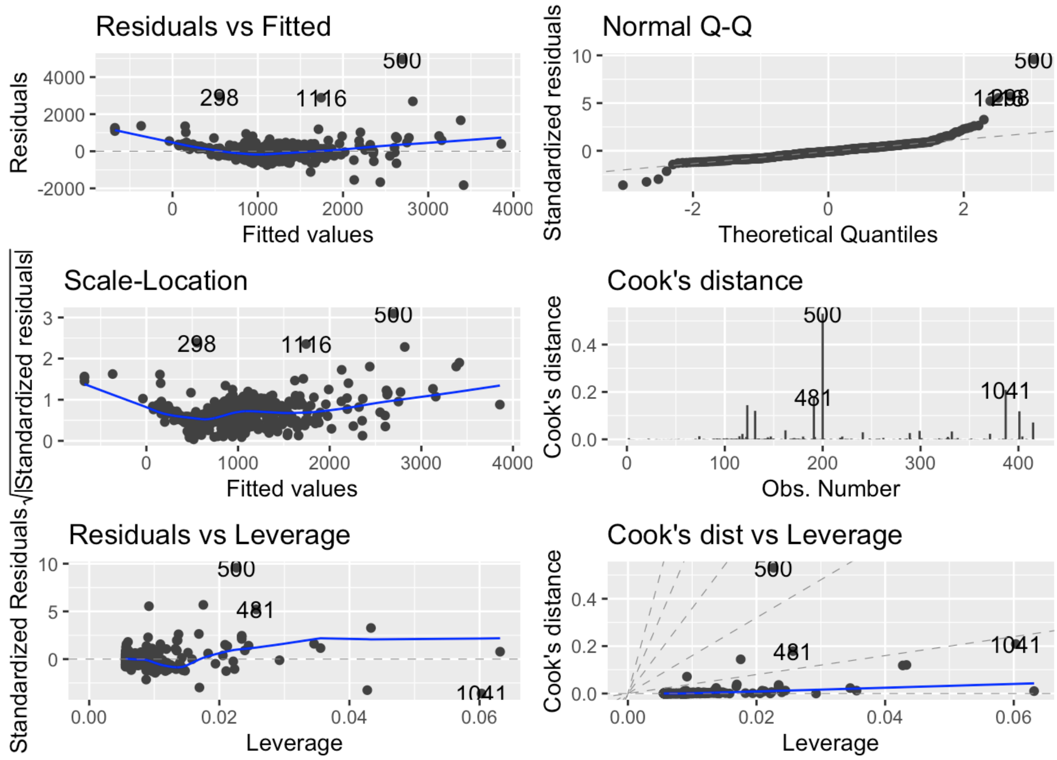
▼ Code

```
# Tidyverse way
ggplot(melbdata.sub |> select(Suburb, Price) |> drop_na())
    aes(x = Suburb, y = Price/1000) + geom_boxplot()
```



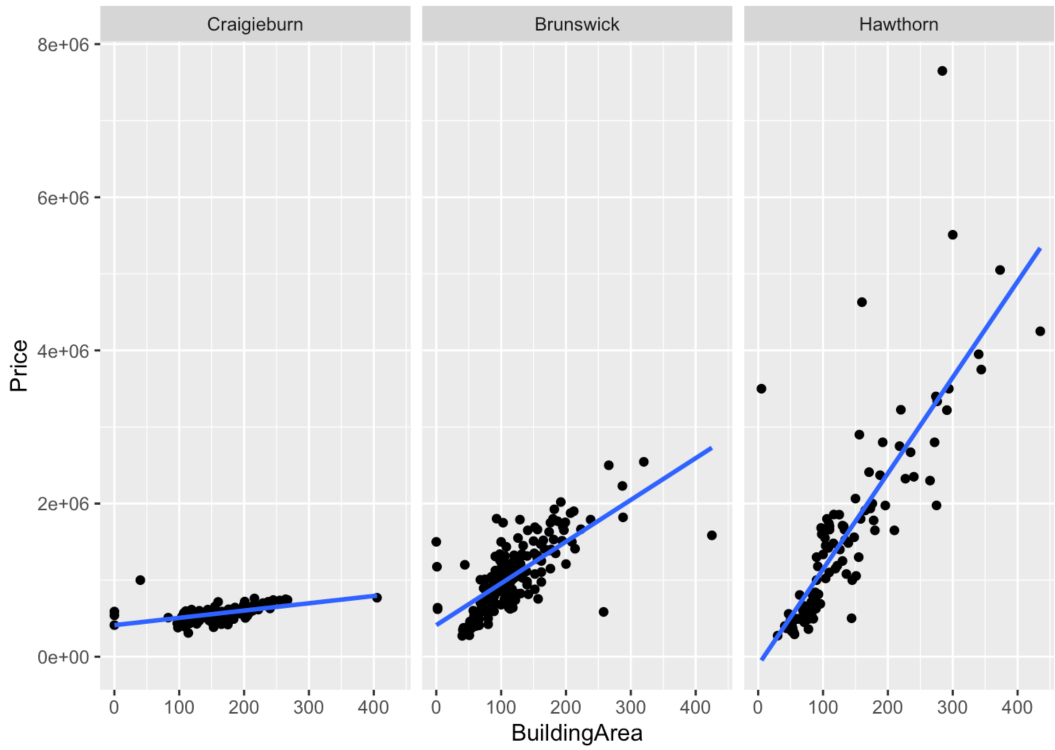
▼ Code

```
lmfit2 <- lm(data = melbdata.sub %>%slice(-c(158,682)), Pr
coefs <- lmfit2$coefficients

autoplot(lmfit2, which = 1:6, nrow = 3, ncol = 2)
```



▼ Code

```
ggplot(melbdata.sub_out |> select(BuildingArea, Price, Sub
    aes(x = BuildingArea, y = Price) +
    geom_point() +
    geom_smooth(formula = y ~ x, method = "lm", se = FALSE
    facet_wrap(~Suburb)
```



▼ Code

```
summary(lmfit2)
```

```
Call:
lm(formula = Price/1000 ~ BuildingArea + Suburb, data =
melbdata.sub %>%
    slice(-c(158, 682)))

Residuals:
    Min      1Q  Median      3Q     Max
-1829.6  -262.7   -41.5   185.2  4953.7

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     -675.6983    80.1195  -8.434 5.71e-16 ***
BuildingArea       7.6864     0.3991  19.260  < 2e-16 ***
SuburbBrunswick  823.6223    63.9521  12.879  < 2e-16 ***
SuburbHawthorn  1189.0488    69.2335  17.174  < 2e-16 ***
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 523.2 on 412 degrees of freedom
  (709 observations deleted due to missingness)
Multiple R-squared:  0.5768,    Adjusted R-squared:  0.5737
F-statistic: 187.2 on 3 and 412 DF,  p-value: < 2.2e-16
```

▼ Code

```
lmfit2 %>% glance()
```

```
# A tibble: 1 × 12
  r.squared adj.r.squa…¹ sigma stati…²  p.value    df logLik
AIC   BIC devia…³
      <dbl>        <dbl> <dbl>   <dbl>    <dbl> <dbl>  <dbl>
<dbl> <dbl>   <dbl>
1     0.577        0.574  523.    187. 1.47e-76     3 -3192.
6395. 6415.  1.13e8
# … with 2 more variables: df.residual <int>, nobs <int>, and
abbreviated
#   variable names ¹adj.r.squared, ²statistic, ³deviance
```

▼ Code

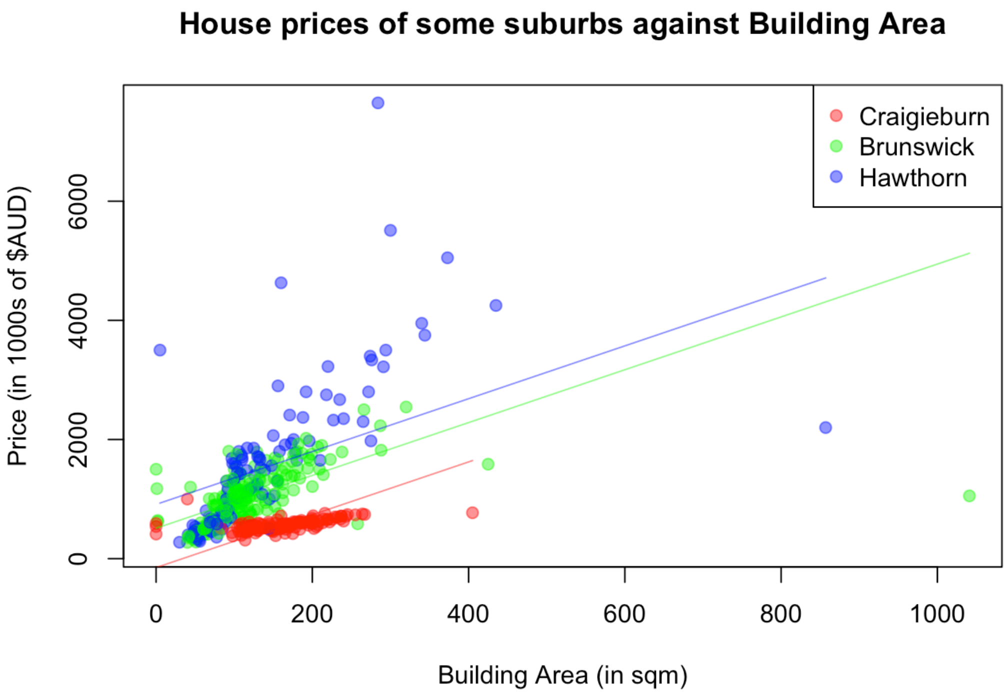
```
r2s <- lmfit2 %>% glance() %>% pull(r.squared)
r2s <- summary(lmfit2)$r.squared
```

One way to highlight that the regression lines for the three suburbs are parallel is to put all three on the same graph, as follows.

▼ Code

```
# Base R
plot(Price/1000 ~ BuildingArea, data = melbdata.sub,
     main = "House prices of some suburbs against Building
     xlab = "Building Area (in sqm)", ylab = "Price (in 10
     col = my.colours[as.integer(melbdata.sub[["Suburb"]])
     pch = 19)
legend("topright", legend = levels(melbdata.sub[["Suburb"]
       col = my.colours, pch = 19)
coefs <- coefficients(lmfit2)
names(my.colours) <- levels(melbdata.sub$Suburb)
r2 <- round(summary(lmfit1)$r.squared, 4)
obs.buildingarea.suburb <- subset(melbdata.sub, select = c
obs.buildingarea.suburb <- na.omit(obs.buildingarea.suburb
buildingarea.by.suburb <- with(obs.buildingarea.suburb, sp
```

```
buildingarea.by.suburb <- lapply(buildingarea.by.suburb, r

invisible(lapply(levels(melbdata.sub$Suburb), function(x)
   pred.df <- data.frame(BuildingArea = buildingarea.by.s
                         Suburb = x)
   lines(pred.df[["BuildingArea"]], predict(lm2, newdata
         col = my.colours[which(levels(obs.buildingarea.s
}))
```



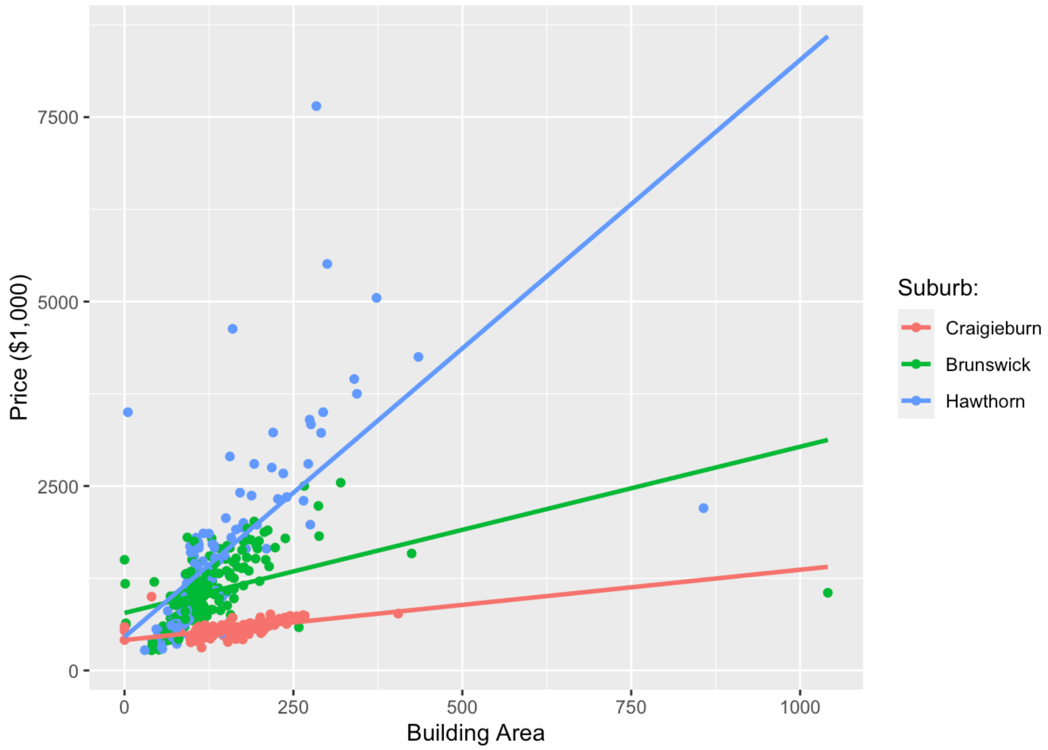
Embedding model fit in ggplot

`ggplot` includes a really clever trick to support easily constructing line fits (smoothed or linear or ...) however the interactions between the model specification and the plotting specification can be subtle, resulting in graphs that do not match the numerical analysis, which are then at best misleading.

An example of fitting different models.

▼ Code

```
###
library(ggplot2)
ggplot(melbdata.sub, aes(x = BuildingArea, y = Price/1000,
  geom_point(na.rm = TRUE) +
  geom_smooth(formula = "y~x", method = "lm", se = FALSE,
  xlab("Building Area") + ylab("Price ($1,000)") + labs(cc
```



Specifying the colour slightly differently, results in a different model!

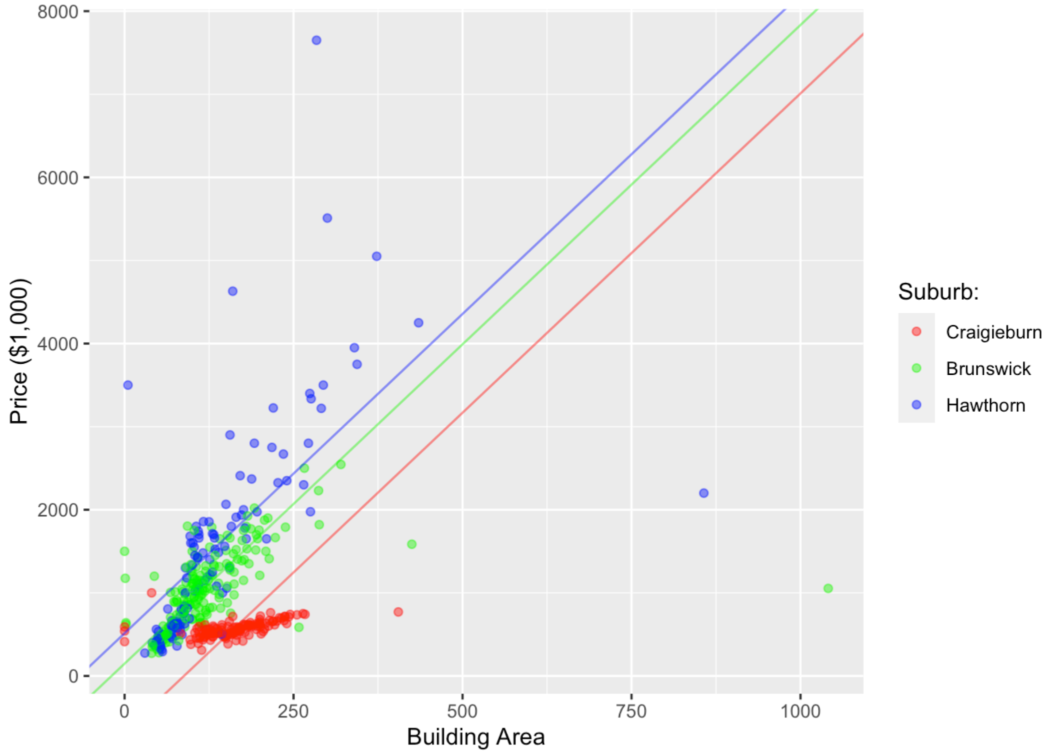
▼ Code

```
ggplot(melbdata.sub, aes(x = BuildingArea, y = Price/1000)
  geom_point(aes(color=Suburb), na.rm = TRUE) +
  geom_smooth(formula="y~x", method = "lm", se = FALSE, fu
  xlab("Building Area") + ylab("Price ($1,000)") + labs(co
```

A simple way to avoid the problem is to make sure that the model being plotted is the original model used for the numerical analysis:

▼ Code

```
### reuse previous color key
colScale <- scale_colour_manual(name = "Suburb:", values =
ggplot(melbdata.sub, aes(x = BuildingArea, y = Price/1000,
  geom_point(na.rm = TRUE) +
  xlab("Building Area") + ylab("Price ($1,000)") + colScal
  sapply(unique(melbdata.sub$Suburb), function(x) {
        int <- coefs[1]
        if (any(adjust.ind <- grepl(paste0(x, "$"), names(c
            int <- int + coefs[adjust.ind]
        geom_abline( intercept=int, slope=coefs[2], col=my.
     })
```



Commentary on Models

The `Suburb` predictor improves the fit of the model by increasing the R^2 from 0.1725 to 0.5767645. However, the adjusted R^2 is amore appropriate goodness of fit measure when there is more than one predictor in the model since adding another predictor will always increase the R^2. In this case the adjusted R^2 increases by a similar amount suggesting Suburb is a good additional predictor.

Interpreting the `BuildingArea` slope has the interpretation that for each unit increase in square meter of building size, the expected average price would increase by $4435. Interpreting the categorical predictors needs to be done by intercept adjustment. The first categorical level of `Suburb` (Brunswick) becomes the baseline intercept and the other suburbs are adjusted against the baseline intercept. In this case Craigieburn and Hawthorn have adjustments of -660,000 and 400,000 respectively. This should be interpretted that properties in Craigieburn are $660,000 cheaper than Brunswick on average (if BuildingArea is held fixed). Hawthorn properties are $400,000 more expensive than Brunswick. This is consistent with the graphical summary in the boxplot which indicates without adjusting for Building Area, Craigie burn tends to have cheaper houses with low variance while Hawthorn has a large variance in house prices with many very expensive outlying properties.

b. Adding the number of car spaces in to the model and compare the goodness of fit measures.

▼ Code

```
lmfit4 <- lm(data = melbdata.sub, Price ~ BuildingArea + S
summary(lmfit4)
```

```
Call:
lm(formula = Price ~ BuildingArea + Suburb + Car, data =
melbdata.sub)

Residuals:
     Min       1Q   Median       3Q      Max
-3417281  -273352   -59191   252474  5001704

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     -447547.1    89421.2  -5.005 8.37e-07 ***
BuildingArea       3761.7      351.3  10.708  < 2e-16 ***
SuburbBrunswick  781107.7    73776.4  10.588  < 2e-16 ***
SuburbHawthorn  1144544.5    78263.7  14.624  < 2e-16 ***
Car              220740.5    34616.8   6.377 4.98e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 588500 on 402 degrees of freedom
  (720 observations deleted due to missingness)
Multiple R-squared:  0.477, Adjusted R-squared:  0.4718
F-statistic: 91.66 on 4 and 402 DF,  p-value: < 2.2e-16
```

Adding car spaces seems to improve the prediction model if `BuildingArea` and `Suburb` are already included in the model. The goodness of fit metrics (both raw and adjusted) increase.

2.5 Impact of outliers

Model construction can be affected by unwanted variation and noise such as outliers. For example, houses with very small building areas of 5sqm and lower and larger places over 300 sqm look like outliers. How would you assess the impact of outliers?

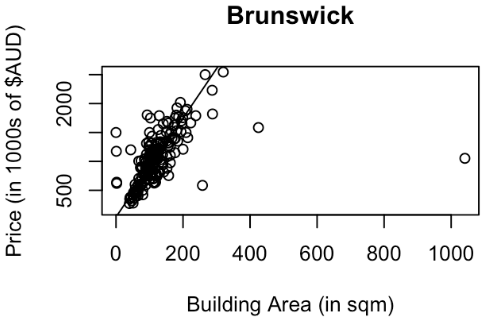
Solution

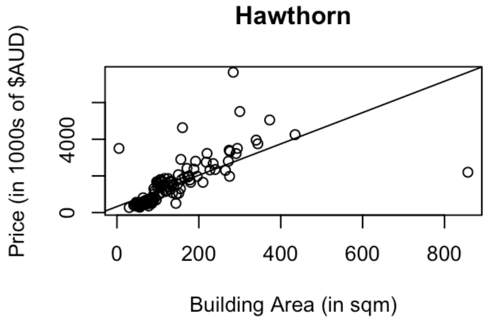
A simple strategy to assess the impact of outliers is to remove the outliers and see if you can improve the prediction model.

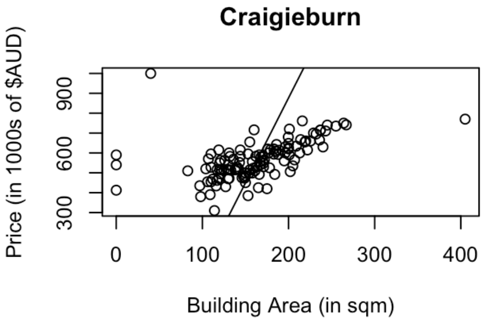
▼ Code

```
melbdata.sub.2 <- subset(melbdata.sub, BuildingArea > 10 &
lmfit3 <- lm(data = melbdata.sub.2, Price/1000 ~ BuildingA
coefs <- lmfit3$coefficients
par(mfrow = c(2, 2))
invisible(lapply(unique(melbdata.sub$Suburb), function(x)
    plot(Price/1000 ~ BuildingArea, data = subset(melbdata
         xlab = "Building Area (in sqm)", ylab = "Price (i
    int <- coefs[1]
    if (any(adjust.ind <- grepl(paste0(x, "$"), names(coef
        int <- int + coefs[adjust.ind]
    abline(int, coefs[2])
}))
summary(lmfit3)
```

```
Call:
lm(formula = Price/1000 ~ BuildingArea + Suburb, data =
melbdata.sub.2)

Residuals:
    Min      1Q  Median      3Q     Max
-1658.0  -260.8   -30.5   192.6  4895.4

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     -832.4033    80.4592  -10.35   <2e-16 ***
BuildingArea       8.5448     0.4234   20.18   <2e-16 ***
SuburbBrunswick  870.8069    56.3822   15.45   <2e-16 ***
SuburbHawthorn  1160.2793    61.6807   18.81   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 442.6 on 396 degrees of freedom
  (81 observations deleted due to missingness)
Multiple R-squared:  0.5984,    Adjusted R-squared:  0.5954
F-statistic: 196.7 on 3 and 396 DF,  p-value: < 2.2e-16
```







Removing the outliers does improve the fit of the model as the overall residual standard error has decreased and the goodness of fit metrics have increased to around 0.6. Also visually we can see an improved fit for Hawthorn and Brunswick. Although there still is a poor fit for Cragieburn

2.6 Prediction

Predict the price of a house in Hawthorn with 2 car spaces and 100 sqm in building area. What is the 95% confidence interval of your prediction value?

Solution

▼ Code

```
predict(lmfit4, data.frame(Suburb = "Hawthorn", BuildingAr
```

```
      fit     lwr     upr
1 1514653 1393868 1635439
```

If using the `lmfit4` model, then the predicted value for an average property with those features would be $1,514,653.