# Exercises solutions

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```
library(tidyverse)
```

### AD1. Investigating populations

The data of interest (Europe and 1992) is extracted from the gapminder dataset. Then a linear model is fitted using the lm command, and the results are examined.

```
library(gapminder)
gapminder_european_data_from_1992 <- gapminder %>%
  filter(year == 1992, continent == 'Europe')
fit <- lm(lifeExp ~ gdpPercap, data = gapminder_european_data_from_1992)
summary(fit)</pre>
```

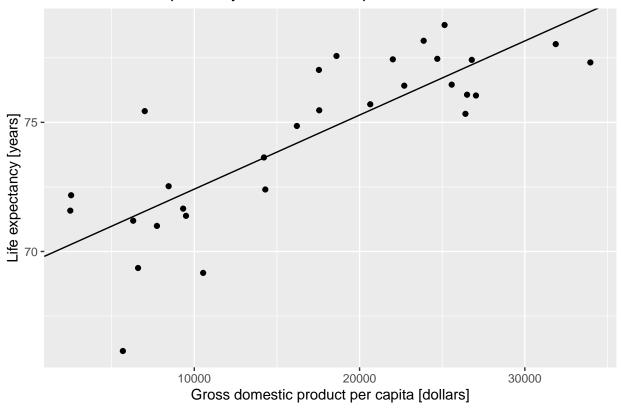
```
##
## lm(formula = lifeExp ~ gdpPercap, data = gapminder_european_data_from_1992)
## Residuals:
      Min
             1Q Median
                              3Q
                                     Max
## -5.0280 -1.0323 0.1025 1.2109 3.8809
##
## Coefficients:
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 6.954e+01 7.447e-01 93.386 < 2e-16 ***
## gdpPercap 2.869e-04 3.865e-05 7.424 4.37e-08 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 1.896 on 28 degrees of freedom
## Multiple R-squared: 0.6631, Adjusted R-squared: 0.6511
## F-statistic: 55.12 on 1 and 28 DF, p-value: 4.373e-08
```

The fitted model has the form

$$lifeExp = 69.5 + 2.87 \times 10^{-4} \cdot gdp$$

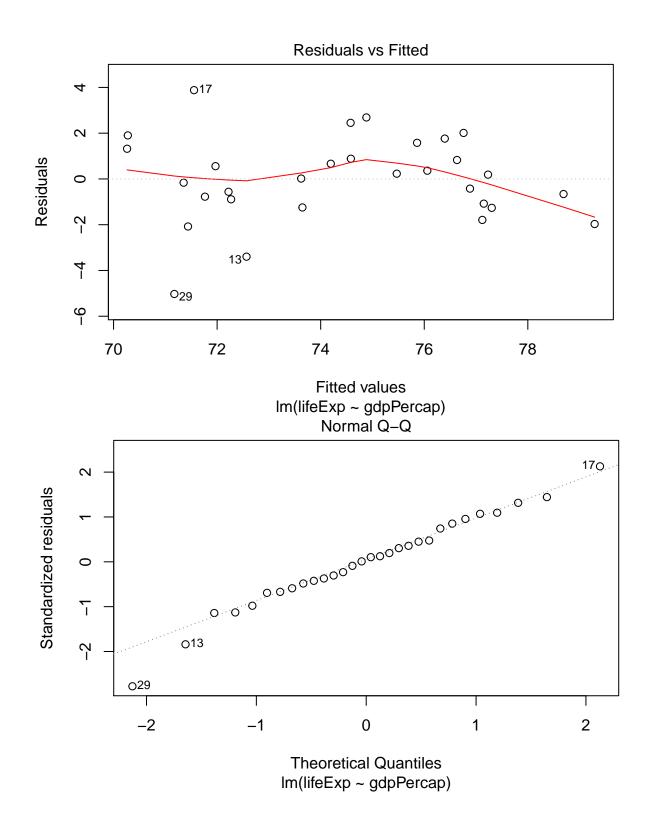
and is shown in the plot below.

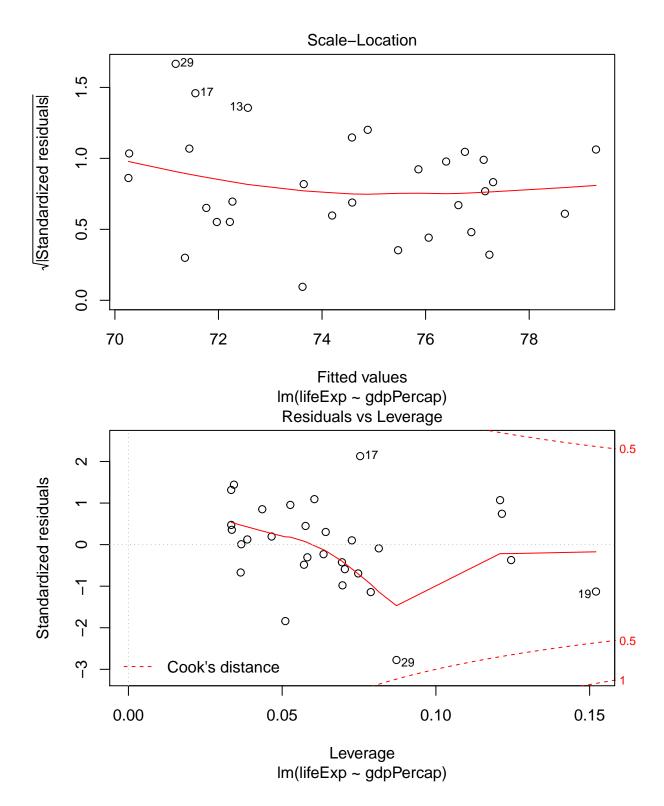
## GDP and Life expectancy in 1992 of European countries



To check the assumptions for making a linear fit, the residuals are inspected. The following things are observed:

```
plot(fit)
```





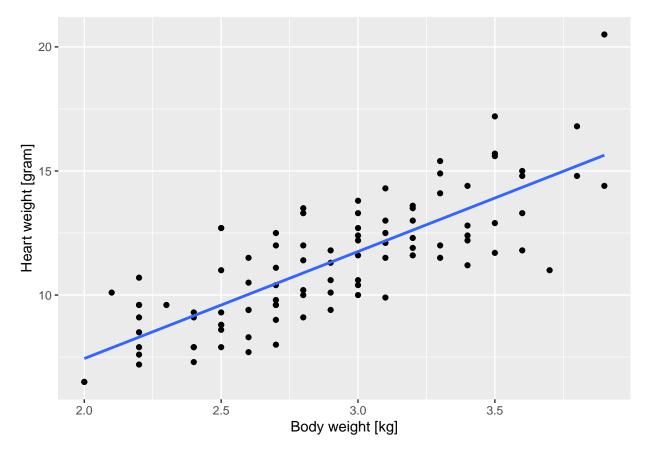
- There is a linera relationship visible in the data
- That the variance in the residuals decreases when the gross domestic product increases.
- The residuals seem to almost follow normal distribution.
- I assume the data is independent.

One of the underlying assumptions for the linear model is that the variance in residuals are uniform over

the input data. This assumption is not met with the given data.

## AD2. Cats body and heart weights

In this section the catsM dataset from the boot package is examined. The dataset contains measures of body and heart weight of a set of male cats.



```
fit <- lm(Hwt ~ Bwt, data = catsM)
fit %>%
summary()
```

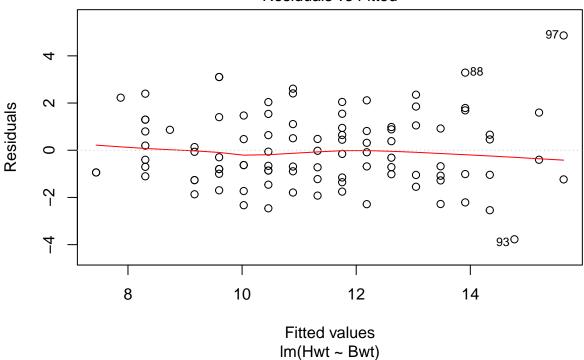
```
##
## Call:
## lm(formula = Hwt ~ Bwt, data = catsM)
##
## Residuals:
```

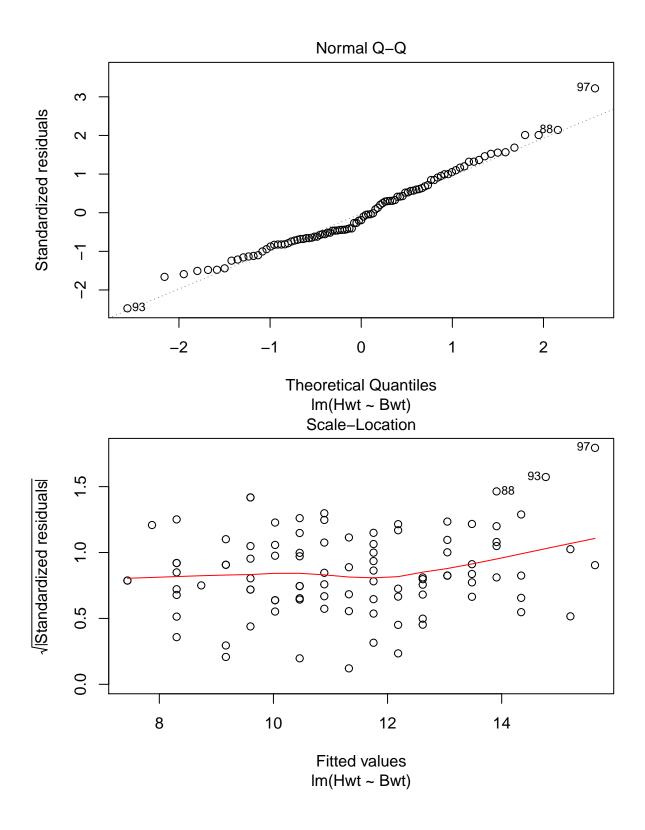
```
##
      Min
               1Q Median
                               3Q
                                      Max
## -3.7728 -1.0478 -0.2976 0.9835
                                  4.8646
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.1841
                           0.9983 -1.186
                                            0.239
## Bwt
                4.3127
                           0.3399 12.688
                                            <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.557 on 95 degrees of freedom
## Multiple R-squared: 0.6289, Adjusted R-squared: 0.625
## F-statistic: 161 on 1 and 95 DF, p-value: < 2.2e-16
```

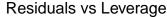
 $hwt = 4.31 \cdot bwt - 1.18$ 

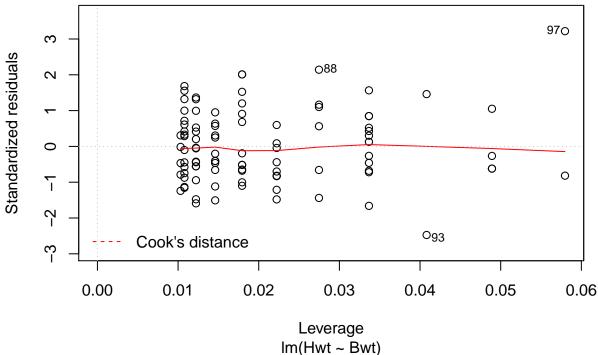
#### plot(fit)

# Residuals vs Fitted









By investigating the residual plots, no violations of the following assumptions is detected

- There is a linear trend in the data
- The residuals are normal distributed (qq plot below)
- Constant variability of the residuals (plot from 3a)
- I assume data points are independent

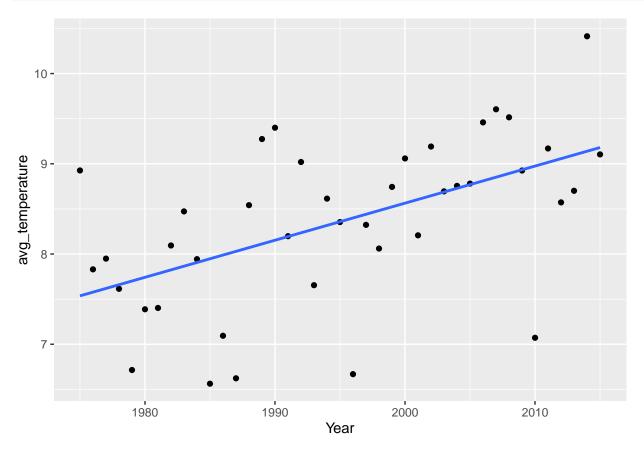
## AD3. Average temperatures

Data about temperatures in different countries are loaded from the file temperatures.csv.

```
## Parsed with column specification:
  cols(
##
##
     tas = col_double(),
##
     Year = col_double(),
     Month = col_double(),
##
##
     Country = col_character(),
##
     ISO3 = col_logical(),
##
     ISO2 = col_logical()
## )
```

Make a linear fit to the average temperature in Denmark from 1975 to 2015.

```
avg_DK <- temperatures %>%
  group_by(Country, Year) %>%
  summarise(avg_temperature = mean(tas)) %>%
  filter(Year >= 1975, Country == "DNK")
ggplot(avg_DK) +
  geom_point(aes(x = Year, y = avg_temperature)) +
  geom_smooth(aes(x = Year, y = avg_temperature), method = lm, se = FALSE)
```



```
fit <- lm(avg_temperature ~ Year, data = avg_DK)
fit %>% summary()
```

```
##
## Call:
## lm(formula = avg_temperature ~ Year, data = avg_DK)
##
## Residuals:
##
                     Median
       Min
                 1Q
                                   ЗQ
                                           Max
## -1.90300 -0.39722 0.01128 0.49561 1.38983
##
## Coefficients:
               Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) -73.62673
                          20.52183 -3.588 0.000919 ***
## Year
                           0.01029
                                   3.995 0.000278 ***
                0.04110
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 0.7793 on 39 degrees of freedom
## Multiple R-squared: 0.2904, Adjusted R-squared: 0.2722
## F-statistic: 15.96 on 1 and 39 DF, p-value: 0.0002779
```

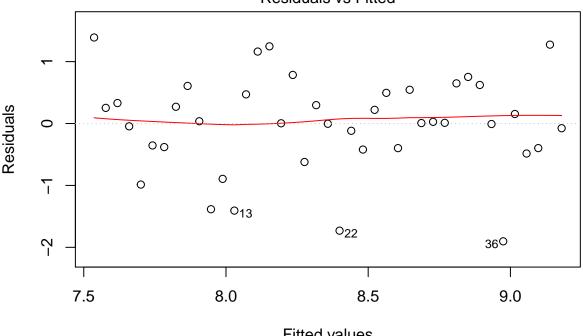
The fitted model has the form

$$temperature = -73.62673 + 0.04110 \cdot year$$

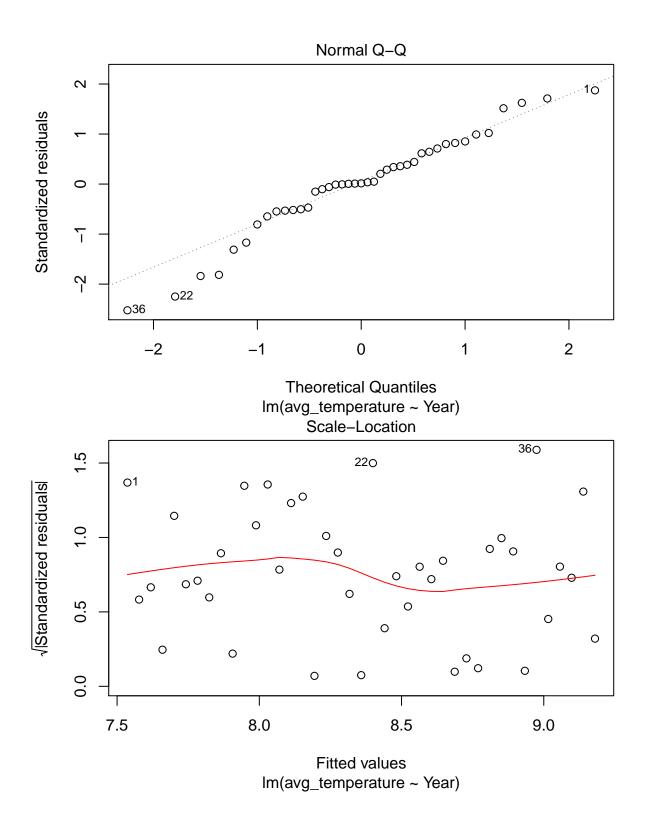
Where the slope of the line (0.04644) has a standard error of 0.01, with associated p value  $6.21 \cdot 10^{-5}$ .

#### plot(fit)

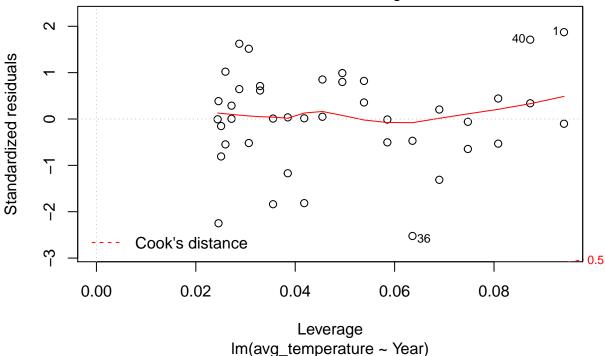
#### Residuals vs Fitted



Fitted values Im(avg\_temperature ~ Year)



#### Residuals vs Leverage



- The linear trend is directly observed when plotting the data.
- The variability is seen to be constant by looking at the residuals over time.
- The residuals are nearly normal distributed, as seen on the qq plot.
- There might be an issue with the requirement of independent observations, as the average temperature from one year potentially can influence the average temperature of the next year.

Predict the average temperature for the year 2030.

```
summary(fit)$coefficients[1] + summary(fit)$coefficients[2]* 2030
```

The average temperature for Denmark in 2030 year (according to the model) should reach 9.8 degrees.

## AD4. Biogas usage over time

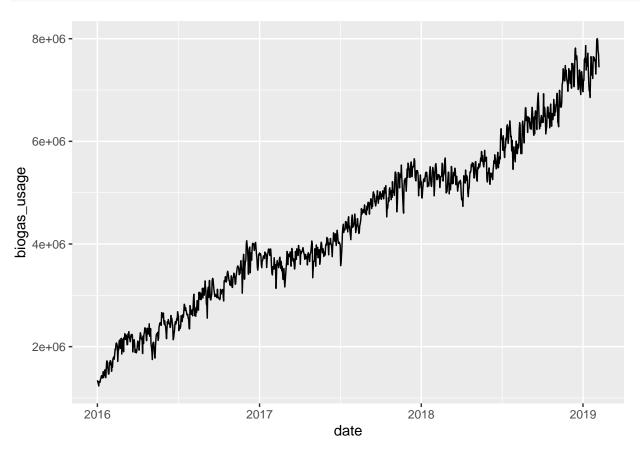
## [1] 9.796564

```
biogas <- readr::read_delim('biogas_usage.csv', delim = ';')

## Parsed with column specification:
## cols(
## date = col_datetime(format = ""),
## year = col_double(),
## daynumber = col_double(),
## biogas_usage = col_double()
## )</pre>
```

To get a sense of the development of the useage of biogas over time, a scatter plot of the *date* and the *biogas\_usage* is inserted below.

```
biogas %>%
   ggplot() +
   geom_line(aes(x = date, y = biogas_usage))
```



Fit a linear model to the biogas consumption. Use day number as the independent variable.

Details from the fitting process is shown below.

```
biogas %>%
  lm(biogas_usage ~ daynumber, data = .) -> biogas_fit
summary(biogas_fit)
```

```
##
## Call:
## lm(formula = biogas_usage ~ daynumber, data = .)
##
## Residuals:
##
                1Q Median
                                ЗQ
       Min
                                       Max
  -917318 -193385
                     -1900 185313 941426
##
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1666647.8
                         17256.4
                                      96.58
                                              <2e-16 ***
                               26.4 182.93
## daynumber
                  4829.0
                                              <2e-16 ***
```

```
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 290600 on 1131 degrees of freedom
## Multiple R-squared: 0.9673, Adjusted R-squared: 0.9673
## F-statistic: 3.346e+04 on 1 and 1131 DF, p-value: < 2.2e-16</pre>
```

Predict the biogas consumption for day number 3650

```
summary(biogas_fit)$coefficients[1] + summary(biogas_fit)$coefficients[2]* 3650
```

## [1] 19292534