

Linear regression and correlation

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1 The regression problem

1.1 We want to predict

- We will study the dataset **trees**, which is on the course website:

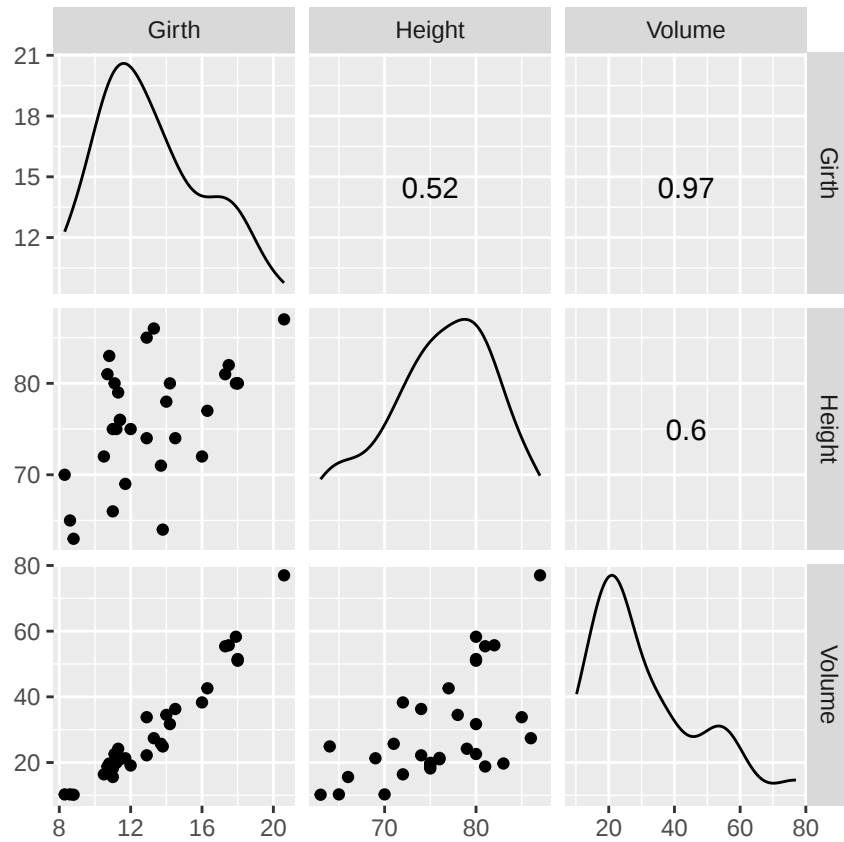
```
trees <- read.delim("https://asta.math.aau.dk/datasets?file=trees.txt")
```

- In this experiment we have measurements of 3 variables for 31 randomly chosen trees:
- **Girth** numeric. Tree diameter in inches.
- **Height** numeric. Height in ft.
- **Volume** numeric. Volume of timber in cubic ft.
- We want to predict the tree volume, if we measure the tree height and/or the tree girth (diameter).
- This type of problem is called **regression**.
- Relevant terminology:
 - We measure a quantitative **response** y , e.g. **Volume**.
 - In connection with the response value y we also measure one (later we will consider several) potential **explanatory** variable x . Another name for the explanatory variable is **predictor**.

1.2 Initial graphics

- Any analysis starts with relevant graphics.

```
library(mosaic)
library(GGally)
ggscatmat(trees) # Scatter plot matrix from GGally package
```



- For each combination of the variables we plot the (x, y) values.
- It looks like **Girth** is a good predictor for **Volume**.
- If we only are interested in the association between two (and not three or more) variables we use the usual `gf_point` function.

1.3 Simple linear regression

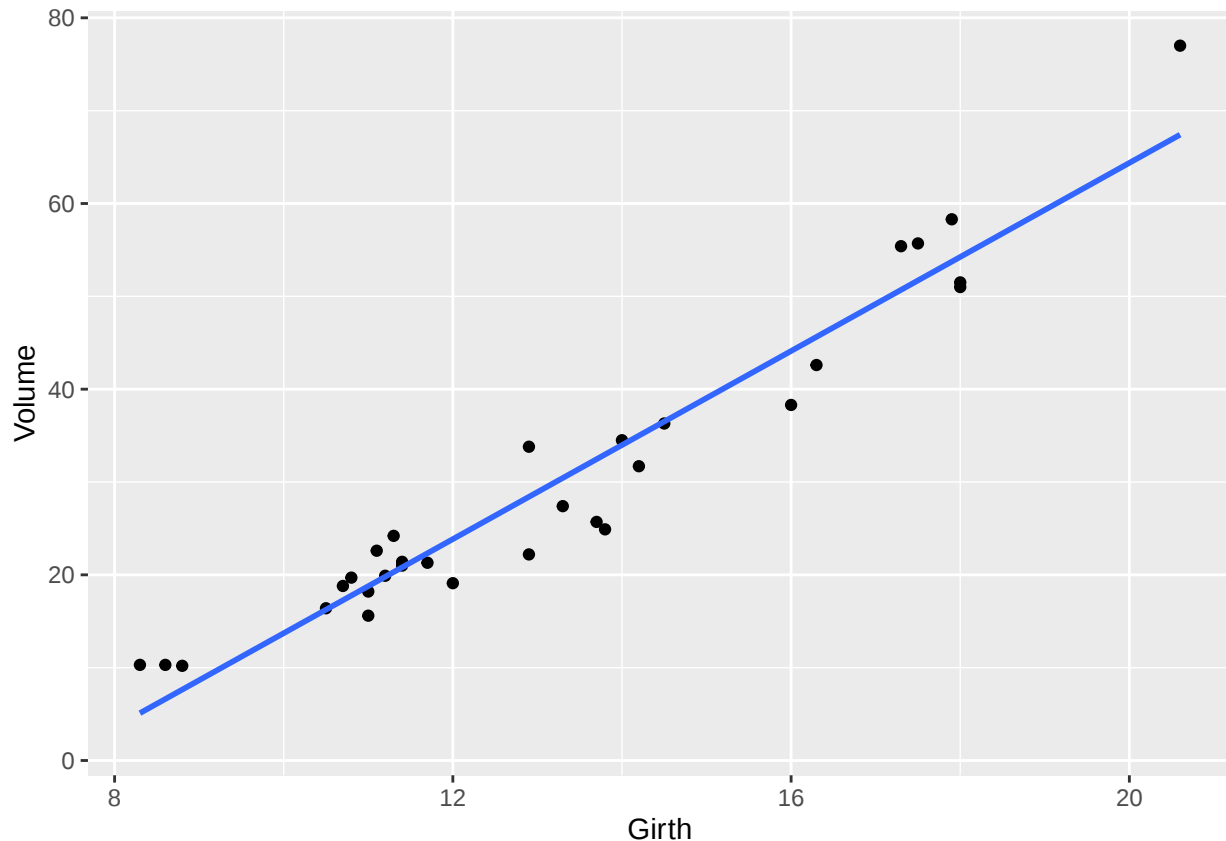
- We choose to use $x = \text{Girth}$ as predictor for $y = \text{Volume}$. When we only use one predictor we are doing **simple regression**.
- The simplest **model** to describe an association between **response** y and a **predictor** x is **simple linear regression**.
- I.e. ideally we see the picture

$$y(x) = \alpha + \beta x$$

where

- α is called the **Intercept** - the line's intercept with the y -axis, corresponding to the response for $x = 0$.
- β is called **Slope** - the line's slope, corresponding to the change in response, when we increase the predictor by one unit.

```
gf_point(Volume ~ Girth, data = trees) %>% gf_lm()
```



1.4 Model for linear regression

- Assume we have a sample with joint measurements (x, y) of predictor and response.
- Ideally the model states that

$$y(x) = \alpha + \beta x,$$

but due to random variation there are deviations from the line.

- What we observe can then be described by

$$y = \alpha + \beta x + \varepsilon,$$

where ε is a **random error**, which causes deviations from the line.

- We will continue under the following **fundamental assumption**:
 - The errors ε are normally distributed with mean zero and standard deviation $\sigma_{y|x}$.
- We call $\sigma_{y|x}$ the **conditional standard deviation** given x , since it describes the variation in y around the regression line, when we know x .

1.5 Least squares

- In summary, we have a model with 3 parameters:
 - (α, β) which determine the line
 - $\sigma_{y|x}$ which is the standard deviation of the deviations from the line.
- How are these estimated, when we have a sample $(x_1, y_1) \dots (x_n, y_n)$ of (x, y) values??
- To do this we focus on the errors

$$\varepsilon_i = y_i - \alpha - \beta x_i$$

which should be as close to 0 as possible in order to fit the data best possible.

- We will choose the line, which minimizes the sum of squares of the errors:

$$\sum_{i=1}^n \varepsilon_i^2 = \sum_{i=1}^n (y_i - \alpha - \beta x_i)^2.$$

- If we set the partial derivatives to zero we obtain two linear equations for the unknowns (α, β) , where the solution (a, b) is given by:

$$b = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad \text{and} \quad a = \bar{y} - b\bar{x}$$

1.6 The prediction equation and residuals

- The equation for the estimates $(\hat{\alpha}, \hat{\beta}) = (a, b)$,

$$\hat{y} = a + bx$$

is called **the prediction equation**, since it can be used to predict y for any value of x .

- Note: The prediction equation is determined by the current sample. I.e. there is an uncertainty attached to it. A new sample would without any doubt give a different prediction equation.
- Our best estimate of the errors is

$$e_i = y_i - \hat{y} = y_i - a - bx_i,$$

i.e. the vertical deviations from the prediction line.

- These quantities are called **residuals**.
- We have that
 - The prediction line passes through the point $(\bar{x}, \bar{y})$.
 - The sum of the residuals is zero.

1.7 Estimation of conditional standard deviation

- To estimate $\sigma_{y|x}$ we need **Sum of Squared Errors**

$$SSE = \sum_{i=1}^n e_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2,$$

which is the squared distance between the model and data.

- We then estimate $\sigma_{y|x}$ by the quantity

$$s_{y|x} = \sqrt{\frac{SSE}{n-2}}$$

- Instead of n we divide SSE with **the degrees of freedom** $df = n - 2$. Theory shows, that this is reasonable.
- The degrees of freedom df are determined as the sample size minus the number of parameters in the regression equation.
- In the current setup we have 2 parameters: (α, β) .

1.8 Example in R

```
model <- lm(Volume ~ Girth, data = trees)
summary(model)
```

```
##
## Call:
## lm(formula = Volume ~ Girth, data = trees)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8.065 -3.107  0.152  3.495  9.587
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -36.9435     3.3651  -10.98 7.62e-12 ***
## Girth         5.0659     0.2474   20.48 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.252 on 29 degrees of freedom
## Multiple R-squared:  0.9353, Adjusted R-squared:  0.9331
## F-statistic: 419.4 on 1 and 29 DF,  p-value: < 2.2e-16
```

- The estimated residuals vary from -8.065 to 9.578 with median 0.152.
- The estimate of **Intercept** is $a = -36.9435$
- The estimate of slope of **Girth** is $b = 5.0659$
- The estimate of the conditional standard deviation (also called residual standard error) is $s_{y|x} = 4.252$ with $31 - 2 = 29$ degrees of freedom.

1.9 Test for independence

- We consider the regression model

$$y = \alpha + \beta x + \varepsilon$$

where we use a sample to obtain estimates (a, b) of (α, β) , an estimate $s_{y|x}$ of $\sigma_{y|x}$ and the degrees of freedom $df = n - 2$.

- We are going to test

$$H_0 : \beta = 0 \quad \text{against} \quad H_a : \beta \neq 0$$

- The null hypothesis specifies, that y **doesn't** depend linearly on x .
- In other words the question is: Is the value of b far away from zero?
- It can be shown that b has standard error

$$se_b = \frac{s_{y|x}}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2}}$$

with df degrees of freedom.

- So, we want to use the test statistic

$$t_{\text{obs}} = \frac{b}{se_b}$$

which has to be evaluated in a t-distribution with df degrees of freedom.

1.10 Example

- Recall the summary of our example:

```
summary(model)
```

```
##
## Call:
## lm(formula = Volume ~ Girth, data = trees)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8.065 -3.107  0.152  3.495  9.587
##
## Coefficients:
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```

- As we noted previously $b = 5.0659$ and $s_{y|x} = 4.252$ with $df = 29$ degrees of freedom.
- In the second column(Std. Error) of the **Coefficients** table we find $se_b = 0.2474$.
- The observed t-score (test statistic) is then

$$t_{\text{obs}} = \frac{b}{se_b} = \frac{5.0659}{0.2474} = 20.48$$

which also can be found in the third column (**t value**).

- The corresponding p-value is found in the usual way by using the t-distribution with 29 degrees of freedom.
- In the fourth column(**Pr(>|t|)**) we see that the p-value is less than 2×10^{-16} . This is no surprise since the t-score was way above 3.

1.11 Confidence interval for slope

- When we have both the standard error and the reference distribution, we can construct a confidence interval in the usual way:

$$b \pm t_{\text{crit}} se_b,$$

where the t-score is determined by the confidence level.

- The t-score can be found using **qdist** in **R**: In our example we have 29 degrees of freedom and with a confidence level of 95% we get $t_{\text{crit}} = \text{qdist}("t", 0.975, df = 29) = 2.045$.
- If you are lazy (like most statisticians are):

```
confint(model)
```

```
##              2.5 %      97.5 %
## (Intercept) -43.825953 -30.060965
## Girth        4.559914   5.571799
```

- i.e. (4.56, 5.57) is a 95% confidence interval for the slope of **Girth**.

1.12 Correlation

- The estimated slope b in a linear regression doesn't say anything about the strength of association between y and x .
- **Girth** was measured in inches, but if we rather measured it in kilometers the slope is much larger: An increase of 1km in **Girth** yield an enormous increase in **Volume**.
- Let s_y and s_x denote the sample standard deviation of y and x , respectively.

- The corresponding t-scores

$$y_t = \frac{y}{s_y} \quad \text{and} \quad x_t = \frac{x}{s_x}$$

are independent of the chosen measurement scale.

- The corresponding prediction equation is then

$$\hat{y}_t = \frac{a}{s_y} + \frac{s_x}{s_y} b x_t$$

- i.e. **the standardized regression coefficient** (slope) is

$$r = \frac{s_x}{s_y} b$$

which also is called **the correlation** between y and x .

- It can be shown that:
 - $-1 \leq r \leq 1$
 - The absolute value of r measures the (linear) strength of dependence between y and x .
 - When $r = 1$ all the points are on the prediction line, which has positive slope.
 - When $r = -1$ all the points are on the prediction line, which has negative slope.
- To calculate the correlation:

```
cor(trees)
```

```
##           Girth    Height    Volume
## Girth  1.0000000 0.5192801 0.9671194
## Height 0.5192801 1.0000000 0.5982497
## Volume 0.9671194 0.5982497 1.0000000
```

- There is a strong positive correlation between **Volume** and **Girth** ($r=0.967$).
- Note, it only works when all columns are numeric. Otherwise the relevant numeric columns should be extracted like this:

```
cor(trees[,c("Height", "Girth", "Volume")])
```

which produces the same output as above.

- Alternatively, one can calculate the correlation between two variables of interest like:

```
cor(trees$Height, trees$Volume)
```

```
## [1] 0.5982497
```

2 R-squared: Reduction in prediction error

2.1 R-squared: Reduction in prediction error

- We want to compare two different models used to predict the response y .
- Model 1: We do not use the knowledge of x , and use $\bar{y}$ to predict any y -measurement. The corresponding prediction error is defined as

$$TSS = \sum_{i=1}^n (y_i - \bar{y})^2$$

and is called the **Total Sum of Squares**.

- Model 2: We use the prediction equation $\hat{y} = a + bx$ to predict y_i . The corresponding prediction error is then the Sum of Squared Errors

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2.$$

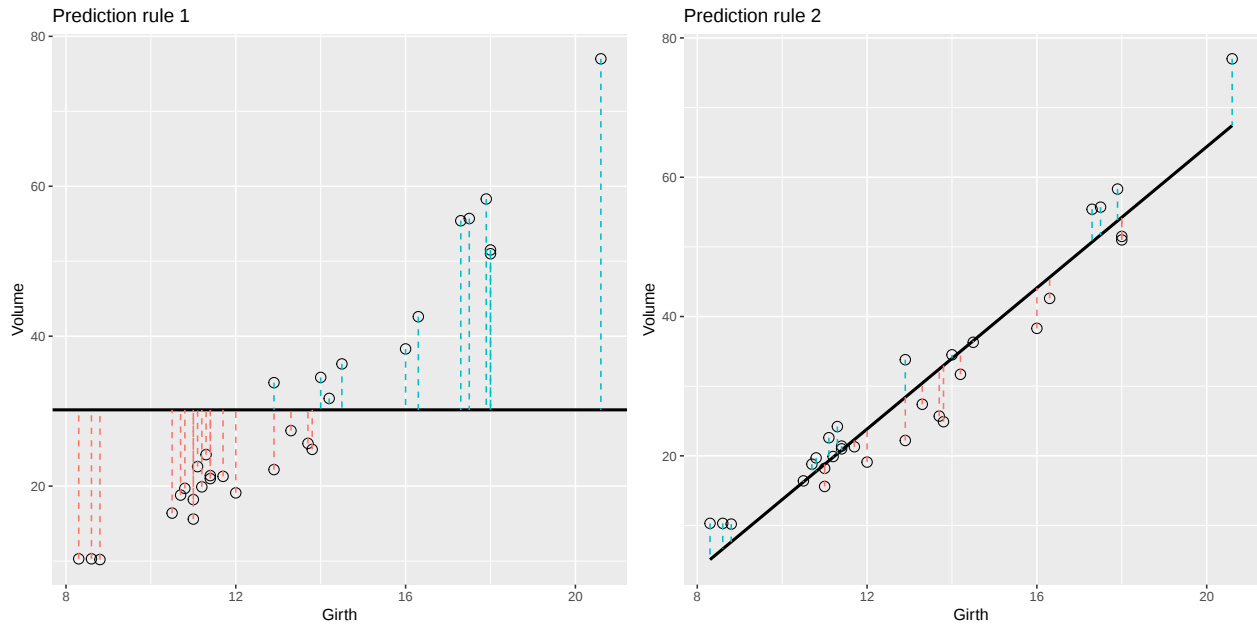
- We then define

$$r^2 = \frac{TSS - SSE}{TSS}$$

which can be interpreted as the relative reduction in the prediction error, when we include x as explanatory variable.

- This is also called the **fraction of explained variation**, **coefficient of determination** or simply **r-squared**.
- For example if $r^2 = 0.65$, the interpretation is that x explains about 65% of the variation in y , whereas the rest is due to other sources of random variation.

2.2 Graphical illustration of sums of squares



- Note the data points are the same in both plots. Only the prediction rule changes.
- The error of using Rule 1 is the total sum of squares $E_1 = TSS = \sum_{i=1}^n (y_i - \bar{y})^2$.
- The error of using Rule 2 is the residual sum of squares (sum of squared errors) $E_2 = SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2$.

2.3 r^2 : Reduction in prediction error

- For the simple linear regression we have that

$$r^2 = \frac{TSS - SSE}{TSS}$$

is equal to the square of the correlation between y and x , so it makes sense to denote it r^2 .

- Towards the bottom of the output below we can read off the value $r^2 = 0.9353 = 93.53\%$, which is a large fraction of explained variation.

```
summary(model)
```

```
##
## Call:
## lm(formula = Volume ~ Girth, data = trees)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
```

```

## -8.065 -3.107  0.152  3.495  9.587
##
## Coefficients:
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```