Regression

Simple Linear regression Morten Frydenberg © Department of Biostatisics, Aarhus Univ, Denmark

Regression in general

Simple linear regression.

The model.

The assumptions.

The parameters.

Estimation.

The distribution of the estimates

Confidence intervals

Changing the reference value and scale for x

Tests

The example: Summarising

Linear and Logistic regression - Note 1.1

Regression in general

A regression model can be many things!

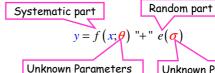
In general it models the relationship between:

y: dependent/response

and a set of

x's: independent/explanatory variables.

The dependent variable is modelled as a function of the independent variable plus some unexplained random variation:



Unknown Parameters

Regression in general

$$y = f(x; \theta) "+" e(\sigma)$$

Some examples:

$$pefr = \beta_0 + \beta_1 \cdot height + E$$

$$pefr = \beta_0 + \beta_1 \cdot height + \beta_2 \cdot height^2 + E$$
 and $E \sim N(0, \sigma^2)$

 $gfr = \exp(\beta_0 + \beta_1 \cdot \ln[Cr]) + E$

$$conc(t) = dose \cdot V \cdot \left[exp(-\lambda_{abs} \cdot t) - exp(-\lambda_{eli} \cdot t) \right] + E$$

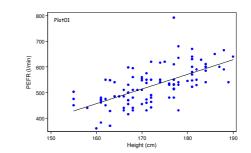
The first two are linear regressions, the last two non-linear.

In this course we will focus on the linear regressions.

Linear and Logistic regression - Note 1.1

Simple linear regression

The relationship between measured *PEFR* and *height* in 101 medical students.



A model:

PEFR = line + some random variation

seems to be valid.

Simple linear regression: The model

Let $PEFR_i$ and $height_i$ be the data for the *i*th person.

$$PEFR_i = \beta_0 + \beta_1 \cdot height_i + E_i \quad E_i \sim N(0, \sigma^2)$$

This model is based on the assumptions:

- 1. The expected value of *PEFR* is a linear function of *height*.
- 2. The unexplained random deviations are independent.
- 3. The unexplained random deviations have the same distributions.
- 4. This distribution is normal.

Simple linear regression: The parameters

$$PEFR_i = \beta_0 + \beta_1 \cdot height_i + E_i \qquad E_i \sim N(0, \sigma^2)$$

The model have three unknown parameters:

- 1. The intercept β_0
- 2. The slope (or regression coefficient) β_1
- 3. The residual variance σ^2 or residual standard deviation σ .

The interpretation of the parameters:

 β_0 is expected *PEFR* of a person with *height*=0.

Obviously, this does not make sense.

We will later look at how one can get a meaningful estimate of the general level of *PEFR*!

Simple linear regression: The parameters

$$PEFR_i = \beta_0 + \beta_1 \cdot height_i + E_i \qquad E_i \sim N(0, \sigma^2)$$

 β_1 is the **expected difference** in *PEFR* for two persons who differ with one unit (here cm) in height.

If a person is 6 cm higher than another, then we will expected that his *PEFR* is $6\beta_1$ higher than the other.

 σ is best understood by the fact that a 95%-prediction interval around the line is given by $\pm 1.96 \sigma$.

Simple linear regression: The estimates (by hand)

$$PEFR_i = \beta_0 + \beta_1 \cdot height_i + E_i$$
 $E_i \sim N(0, \sigma^2)$

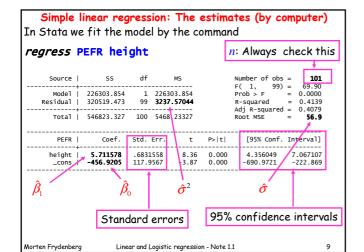
The estimates of the parameters are found by the method of least square, which, for this model, is equivalent to the maximum likelihood method.

The estimates can be calculated in hand, but they are of course found much easier by using a computer program.

$$\hat{\beta}_{1} = \frac{\sum (y_{i} - \overline{y})(x_{i} - \overline{x})}{\sum (x_{i} - \overline{x})^{2}} \qquad \hat{\beta}_{0} = \overline{y} - \hat{\beta}_{1} \cdot \overline{x}$$

$$\hat{\beta}_0 = \overline{y} - \hat{\beta}_1 \cdot \overline{x}$$

$$\hat{\sigma}^{2} = \frac{1}{n-2} \sum (y_{i} - \hat{\beta}_{0} - \hat{\beta}_{1} \cdot x_{i})^{2} = \frac{1}{n-2} \sum r_{i}^{2}$$



Simple linear regression: The distribution of the estimates

$$\hat{\boldsymbol{\beta}}_{1} \sim N\left(\boldsymbol{\beta}_{1}, \boldsymbol{\sigma}^{2} \frac{1}{\sum (x_{i} - \overline{x})^{2}}\right)$$
 $\operatorname{se}\left(\hat{\boldsymbol{\beta}}_{1}\right) = \hat{\boldsymbol{\sigma}}/\sqrt{\sum}$

$$\hat{\boldsymbol{\beta}}_{0} \sim N\left(\boldsymbol{\beta}_{0}, \boldsymbol{\sigma}^{2} \left[\frac{1}{n} + \frac{\overline{x}^{2}}{\sum (x_{i} - \overline{x})^{2}} \right] \right) \operatorname{se}\left(\hat{\boldsymbol{\beta}}_{0}\right) = \hat{\boldsymbol{\sigma}} \sqrt{\frac{1}{n} + \frac{\overline{x}^{2}}{\sum (x_{i} - \overline{x})^{2}}}$$

$$\left|\hat{\sigma}^2 \sim \frac{\sigma^2}{n-2} \chi^2 (n-2)\right|$$

The precision of the estimates of β_1 and β_0 depends on the size of the variation around the line.

The precision of the estimate of β_1 increases with the variation of x's

Linear and Logistic regression - Note 1.1

Simple linear regression: Confidence intervals

Exact 95% confidence intervals, CI's, for β_0 and β_1 are found from the estimates and standard errors

95% CI for
$$\beta_1: \hat{\beta}_1 \pm t_{n-2}^{0.975} \cdot \operatorname{se}(\hat{\beta}_1)$$

95% CI for
$$\beta_0$$
: $\hat{\beta}_0 \pm t_{n-2}^{0.975} \cdot \operatorname{se}(\hat{\beta}_0)$

Where $t_{n-2}^{0.975}$ is the upper 97.5 percentile in the tdistribution n-2 degrees of freedom.

These confidence intervals are found in the output.

Note that if n is large then this percentile is close to 1.96and one can use the approximate confidence intervals:

Approx. 95% CI for
$$\beta_1: \hat{\beta}_1 \pm 1.96 \cdot se(\hat{\beta}_1)$$

Approx. 95% CI for
$$\beta_0$$
: $\hat{\beta}_0 \pm 1.96 \cdot \text{se}(\hat{\beta}_0)$

Linear and Logistic regression - Note 1.1

Simple linear regression: Confidence intervals

Exact 95% confidence intervals , CI's, for σ using the χ^2 distribution with n-2 degrees of freedom.

95% CI for
$$\sigma: \hat{\sigma} \cdot \sqrt{\frac{n-2}{\chi_{n-2}^2(0.975)}} \le \sigma \le \hat{\sigma} \cdot \sqrt{\frac{n-2}{\chi_{n-2}^2(0.025)}}$$

Where $\chi_{n-2}^2(0.975)$ is the **upper** 97.5 percentile and $\chi^2_{\scriptscriptstyle n-2} (0.025)$ the lower 2.5 percentile in the χ^2 distribution n-2 degrees of freedom.

This confidence interval is rarely given in the output!

Using Stata we find:

display 56.9*sqrt(99/invchi2(99,0.975)) 49.95859

display 56.9*sqrt(99/invchi2(99,0.025)) 66.099322

Linear and Logistic Regression: Note 1.1

Changing the reference value and scale for x

 $PEFR_i = \beta_0 + \beta_1 \cdot height_i + E_i$ $E_i \sim N(0, \sigma^2)$

In this model the parameter β_0 does not make sense.

But if we consider the **equivalent** model:

$$PEFR_i = \alpha_0 + \alpha_1 \cdot (height_i - 170cm) + E_i \quad E_i \sim N(0, \tau^2)$$

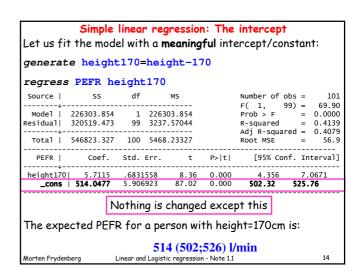
then α_0 is the expected *PEFR* of a person with height 170cm.

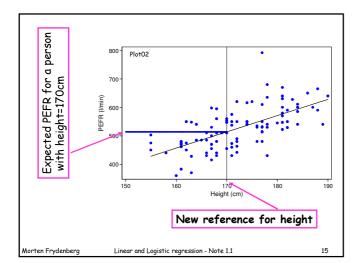
The two other parameters are unchanged, i.e. $\beta_1 = \alpha_1$ and $\sigma = \tau$.

If HEIGHT denote the height in m, i.e. HEIGHT = height/100and we consider the equivalent model:

$$\begin{split} PEFR_i &= \gamma_0 + \gamma_1 \cdot HEIGHT_i + E_i \quad E_i \sim N\left(0, \omega^2\right) \\ \text{then } \gamma_1 &= 100 \cdot \beta_1 \ , \quad \gamma_0 = \beta_0 \ \text{and} \quad \omega = \sigma \end{split}$$

Morten Frydenberg Linear and Logistic regression - Note 1.1





Confidence interval for the estimated line

The **true line** is given as:

and **estimated** by plugging in the estimates

The standard error of this estimate is given by:

$$\operatorname{se}\left(\hat{\beta}_{0} + \hat{\beta}_{1} \cdot x\right) = \hat{\sigma}\sqrt{\frac{1}{n} + \frac{\left(x - \overline{x}\right)^{2}}{\sum\left(x_{i} - \overline{x}\right)^{2}}}$$

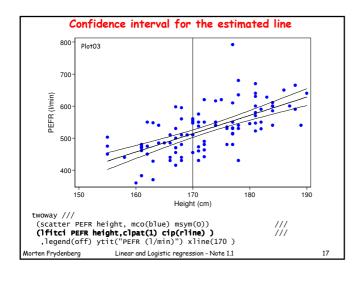
with the 95% (pointwise) confidence interva

$$\hat{\beta}_0 + \hat{\beta}_1 \cdot x \pm t_{n-2}^{0.975} \cdot \operatorname{se}\left(\hat{\beta}_0 + \hat{\beta}_1 \cdot x\right)$$

Many programs can make a plot with the fitted line and its confidence limits.

In Stata its done by the *Ifitci* graph command.

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Simple linear regression: Tests

Statistical test concerning β_0 and β_1 can be calculated in the standard way based on estimates, standard errors and the t-distribution:

 $\beta_1 = \beta_{1H}$ Hypothesis:

Test statistics: $z = \frac{\hat{\beta}_{l} - \beta_{lH}}{\operatorname{se}(\hat{\beta}_{l})}$ P-value: $2 \cdot P(t_{n-2} < -|z|)$

An example: Hypothesis $\beta_1 = 5$

 $z = \frac{5.712 - 5}{0.6832} = 1.04$ P-value 30%

7incom height170-5 In Stata:

Linear and Logistic regression - Note 1.1

Simple linear regression: Tests/confidence intervals

The p-values found in the regression output corresponds to the hypothesis that the given parameter is zero, e.g. $\beta_1 = 0$.

In the example we find that β_1 is highly significant (p<0.001) different from 0.

That is, there is a statistical significant association between PEFR and Height.

The estimate with confidence interval does of course contain much more information than the p-value:

95% CI for
$$\beta_1$$
: 5.71 (4.36;7.07) l/min/cm

From this we can se that the difference in mean PEFR between two persons, who differ one cm in height, is in interval from 4.36 to 7.07 l/min.

Linear and Logistic regression - Note 1.1

The example: Summarising

 $PEFR_i = \beta_0 + \beta_1 \cdot (height_i - 170) + E_i \quad E_i \sim N(0, \sigma^2)$

The estimates:

5.71 (**4.36**;**7.07**) l/min/cm

514 (502;526) l/min 56.9 (50.0;66.1) l/min

The difference in **mean PEFR** between two persons who **differ** one cm in height is in interval from 4.36 to 7.07 l/min - the best guess is 5.71 l/min.

The mean PEFR for a person who is 170 cm is in the interval 502 to 526 l/min - the best guess is 514 l/min.

A 95% prediction interval is given as ± 112 l/min.

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