

Multiple linear regression 1

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Why do we need multiple linear regression.

An example

Interpretation of the parameters

The general model

- The assumptions.
- The parameters.
- Estimation.
- The distribution of the estimates
- Confidence intervals
- The F-test , R-squared

Checking the model

- Fitted values, residuals and leverage
- Extending the model

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Linear and Logistic regression - Note 2.1

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Why do we need a multiple regression

The simple linear regression model only models how the dependent variable, y , depend on **one** independent variable (covariate) , x_1 .

We are often interested in **how** several independent variables, $x_1, x_2, \dots, x_k$, influence the dependent variable , y .

Sometimes we want to **adjust** the influence of some of the information, such as age and sex, before we look at the 'effect' of other variables.

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A multiple linear regression model

We will here start by considering a **random** subsample consisting of 200 persons from the Frammingham data set used in the book.

A **multiple** linear regression model:

$$\ln(sbp) = \beta_0 + \beta_1 \cdot age + \beta_2 \cdot woman + \beta_3 \cdot \ln(bmi) + E$$

Where the **errors**, E , are assumed to be **independent** and **normal** with mean zero and standard deviation σ .

Note, that variable $woman$ is a **dummy**/indicator variable, that it is

- one** if the person is a **woman** and
- zero** if it is a **man**.

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Interpretation of the coefficients 0 - the constant

$$\ln(sbp) = \beta_0 + \beta_1 \cdot age + \beta_2 \cdot woman + \beta_3 \cdot \ln(bmi) + E$$

The first coefficient (the constant term) is the **expected** $\ln(sbp)$ for

a man	(that is ok!)
$age=0$	??????
$bmi=1 \text{ kg/m}^2$	?????? ($\ln(1)=0$).

As in the simple linear regression this not of any interest.

But again we can control the interpretation, by choosing **relevant reference** values for age and bmi . E.g.

$$\ln(sbp) = \alpha_0 + \beta_1 \cdot (age - 45) + \beta_2 \cdot woman + \beta_3 \cdot \ln\left(\frac{bmi}{25}\right) + E$$

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Interpretation of the coefficients 1

$$\ln(sbp) = \beta_0 + \beta_1 \cdot age + \beta_2 \cdot woman + \beta_3 \cdot \ln(bmi) + E$$

The **expected** $\ln(sbp)$ for a **man** with $bmi=27 \text{ kg/m}^2$ is:

$$\beta_0 + \beta_1 \cdot age + \beta_3 \cdot \ln(27)$$

The **expected** $\ln(sbp)$ for another **man** with the same bmi , but **1.7 year older**:

$$\beta_0 + \beta_1 \cdot (age + 1.7) + \beta_3 \cdot \ln(27)$$

The difference is: $1.7\beta_1$

We see that this difference

- does not** depend on the age of the first man.
- does not** depend on the bmi as long as it is the same for the two men.
- would be the same if the two persons were women.

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Interpretation of the coefficients 2

$$\ln(sbp) = \beta_0 + \beta_1 \cdot age + \beta_2 \cdot woman + \beta_3 \cdot \ln(bmi) + E$$

The **expected** $\ln(sbp)$ for a **50 year old man** with $bmi=27 \text{ kg/m}^2$ is:

$$\beta_0 + \beta_1 \cdot 50 + \beta_3 \cdot \ln(27)$$

The **expected** $\ln(sbp)$ for **woman** with the same age and bmi

$$\beta_0 + \beta_1 \cdot 50 + \beta_2 + \beta_3 \cdot \ln(27)$$

The difference is: β_2

We see that this difference

- does not** depend on the age as long as it is the same for the two persons.
- does not** depend on the bmi as long as it is the same for the two persons.

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Interpretation of the coefficients 3

$$\ln(sbp) = \beta_0 + \beta_1 \cdot age + \beta_2 \cdot woman + \beta_3 \ln(bmi) + E$$

The **expected** $\ln(sbp)$ for a **woman** who is 50 year old:

$$\beta_0 + \beta_1 \cdot 50 + \beta_2 + \beta_3 \cdot \ln(bmi)$$

The **expected** $\ln(sbp)$ for another **woman** with the same age, but with a **bmi** which is 10% higher:

$$\beta_0 + \beta_1 \cdot 50 + \beta_2 + \beta_3 \cdot \ln(1.1 \cdot bmi)$$

The difference $\beta_3 \cdot [\ln(1.1 \cdot bmi) - \ln(bmi)] = \beta_3 \cdot \ln(1.1)$

We see that this difference

• **does not** depend on the **bmi** of the first woman.

• **does not** depend on the **age** as long as it is the same for the two women.

• would be the same if the two persons were **men**.

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Interpretation of the coefficients 4

$$\ln(sbp) = \beta_0 + \beta_1 \cdot age + \beta_2 \cdot woman + \beta_3 \ln(bmi) + E$$

$$\beta_3 \cdot [\ln(1.1 \cdot bmi) - \ln(bmi)] = \beta_3 \cdot \ln(1.1)$$

As the **bmi** is introduced on the **log-scale**, then "differences" of this variable is measured **relatively**.

So comparing a pair of persons how **only** differ in **bmi**.

One having **bmi**=25 kg/m² and the other **bmi**=27 kg/m².

Then the expected difference in $\ln(sbp)$ is:

$$\beta_3 \cdot \ln\left(\frac{27}{25}\right) = \beta_3 \cdot 0.077$$

If the **bmi**'s were 21 kg/m² and

23 kg/m², then the expected

difference in $\ln(sbp)$ would be:

$$\beta_3 \cdot \ln\left(\frac{23}{21}\right) = \beta_3 \cdot 0.091$$

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Interpretation of the coefficients 5

$$\ln(sbp) = \beta_0 + \beta_1 \cdot age + \beta_2 \cdot woman + \beta_3 \ln(bmi) + E$$

Taking the **exponential** we get:

$$sbp = \gamma_0 \cdot \gamma_1^{age} \cdot \gamma_2^{woman} \cdot bmi^{\beta_3} \cdot \exp(E)$$

where $\gamma_0 = \exp(\beta_0)$, $\gamma_1 = \exp(\beta_1)$ and $\gamma_2 = \exp(\beta_2)$

That is a non-linear model on the **sbp** scale!

The error is **multiplicative**.

As **medians** are preserved by the exponential transformation then the estimates telling of **effect on the median sbp**.

An example: The age and bmi adjusted median is a factor γ_2 higher for man than for women.

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The multiple linear regression in general

Y the **dependent** variable

$(x_1, x_2, \dots, x_k)$ the **independent** variables.

$$Y = \beta_0 + \sum_{p=1}^k \beta_p \cdot x_p + E \quad E \sim N(0, \sigma^2)$$

This model is based on the **assumptions**:

1. The **expected** value of Y is $\beta_0 + \sum_{p=1}^k \beta_p \cdot x_p$
2. The **unexplained** random deviations are **independent**.
3. The unexplained random deviations have the **same distributions**.
4. This distribution is **normal**.

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The multiple linear regression in general

$$Y = \beta_0 + \sum_{p=1}^k \beta_p \cdot x_p + E \quad E \sim N(0, \sigma^2)$$

We see that the assumptions fall is **two parts**:

The **first concerning** the systematic part

and the three other which focus on the error, the unexplained random variation.

Before we turn to how one can check some of the assumptions we will take a closer look at the first assumption.

The **expected** value of Y is $\beta_0 + \sum_{p=1}^k \beta_p \cdot x_p$

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The assumption of linearity

The **expected** value of Y is $\beta_0 + \sum_{p=1}^k \beta_p \cdot x_p$

This is based on three (sub) assumptions:

- a. Additivity:** The contribution from each of the independent variables are **added**.
- b. Proportionality:** The contribution from independent variables is **proportional** to it is value (with a factor β)
- c. No effectmodification:** The contribution from one independent variables is **the same** whatever the values are for the other.

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The assumption of linearity

The **expected** value of Y is $\beta_0 + \sum_{p=1}^k \beta_p \cdot x_p$

If one consider two persons who differ with Δx_1 in x_1 , Δx_2 in x_2 ... and Δx_k in x_k then difference in the **expected** value of Y is :

$$\sum_{p=1}^k \beta_p \cdot \Delta x_p$$

Again we see that the **contribution** for each of the explanatory variables:

- are **added**,
- are **proportional** to the difference
- and **does not dependent** of the differences in the other

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Estimation

It is almost impossible to find the estimates by hand, but easy if you use a computer.

In STATA: `regress lnSBP age45 woman lnBMI25`

(Note first we have to generate `lnSBP`, `age45`, `woman` and `lnBMI25`)

Source	SS	df	MS		Number of obs =
Model	1.05572698	3	.351908994		200
Residual	4.18969066	196	.021375973		F(3, 196) = 16.46
Total	5.24541764	199	.026358883		Prob > F = 0.0000
					R-squared = 0.2013
					Adj R-squared = 0.1890
					Root MSE = .14621

lnSBP	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
woman	.0036329	.0208905	0.17	0.862	-.0375662 .0448319
age45	.0065384	.0012844	5.09	0.000	.0040053 .0090715
lnBMI25	.2583399	.0758295	3.41	0.001	.1087934 .4078864
_cons	4.856592	.0154266	314.82	0.000	4.826169 4.887016

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Estimation

The last part of the output:

No CI for σ !
It can be calculated by hand

$\hat{\sigma}$
Root MSE = .14621

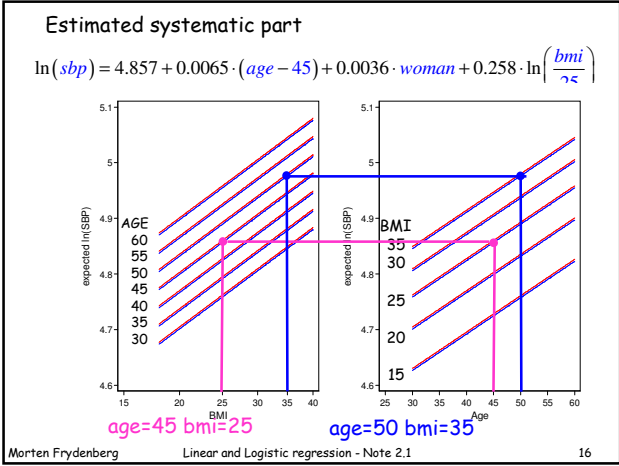
lnSBP	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
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_cons	4.856592	.0154266	314.82	0.000	4.826169 4.887016

the $\hat{\beta}$'s the se's The CI's

Test for $\beta_2=0$

The hypothesis: "no difference in $\ln(\text{sbp})$ between men and women **adjusted** for age and bmi"

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The distribution of the estimates

It can be shown that the **estimates of the coefficients** have **normal** distributions, with **means** equal to the **true values**.

The formulas for the standard deviation of the estimates are **complicated**, but they are estimated by the **standard errors** given in the output.

The estimated standard deviation of the errors is given by:

$$\hat{\sigma}^2 \sim \frac{\sigma^2}{n-k-1} \chi^2(n-k-1)$$

Which gives the confidence interval:

$$95\% \text{ CI for } \sigma: \hat{\sigma} \cdot \sqrt{\chi_{n-k-1}^2(0.975)} \leq \sigma \leq \hat{\sigma} \cdot \sqrt{\chi_{n-k-1}^2(0.025)}$$

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Confidence intervals

Just like in the simple regression we get :
(except we have $n+k-1$ degrees of freedom).

Exact 95% confidence intervals , CI's, for β_p is found from the estimates and standard errors

$$95\% \text{ CI for } \beta_p: \hat{\beta}_p \pm t_{n-k-1}^{0.975} \cdot \text{se}(\hat{\beta}_p)$$

Where $t_{n-k-1}^{0.975}$ is the upper 97.5 percentile in the t-distribution $n-k-1$ degrees of freedom.

These confidence intervals are found in the output.

Note that if $n-k-1$ is large then this percentile is close to **1.96** and one can use the **approximate confidence intervals**:

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

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The ANOVA table and the F-test

The first part of the output:

An analysis of variance table dividing the variation in y in two components: explained by the model (i.e. the 3 variables) and the residual (the rest)

Source	SS	df	MS
Model	1.05572698	3	.351908994
Residual	4.18969066	196	.021375973
Total	5.24541764	199	.026358883

Number of obs = 200
F(3, 196) = 16.46
Prob > F = 0.0000
R-squared = 0.2013
Adj R-squared = 0.1890
Root MSE = .14621

A F-test testing the hypothesis: "all (except β_0) is zero."

Here the test is highly significant: The model explains a statistically significant part of the variation in y !

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The F-test and R-squared

The F- test calculated as: $F = \frac{0.35519}{0.02138} = 16.16$

Source	SS	df	MS
Model	1.05572698	3	.351908994
Residual	4.18969066	196	.021375973
Total	5.24541764	199	.026358883

Number of obs = 200
F(3, 196) = 16.46
Prob > F = 0.0000
R-squared = 0.2013
Adj R-squared = 0.1890
Root MSE = .14621

And under the hypothesis it follows an F-distribution with 3 and 196 degrees of freedom.

The R-squared is the amount of the total variation explained by the model(=1.0557/5.2454).

As this will increase if we include more variables in the model one can look at the adjusted R-squared.

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Predicted values, residuals and leverages

$$Y = \beta_0 + \sum_{p=1}^k \beta_p \cdot x_p + E \quad E \sim N(0, \sigma^2)$$

As in the simple linear regression on can find predicted values, residuals, leverages and standardized residuals:

Predicted value : $\hat{y}_i = \hat{\beta}_0 + \sum_{p=1}^k \hat{\beta}_p \cdot x_{pi}$

Residual: $r_i = y_i - \hat{y}_i = y_i - \sum_{p=1}^k \hat{\beta}_p \cdot x_{pi}$

Leverage : $h_i = \text{a complicated formula}$

Standardized-Residual: $z_i = \frac{r_i}{\hat{\sigma} \sqrt{1-h_i}}$

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Leverage

Although the formula the leverage is complicated, the interpretation of leverage is the same:

A high leverage indicates that the data point has extreme values of the explanatory variables and hence a high influence on the estimates.

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Checking the model 1:

As model is much more complicated than the simple linear regression checking the model is also complicated

Again assumption no. 2: the errors should be independent, is mainly checked by considering how the data was collected.

The distribution of the error is checked by the same type of plot as for the simple linear regression.

- Histogram and qq-plot of the residuals.
- Plots of residuals versus fitted
- Plots of residuals versus each of the explanatory variables.

Data points that stick out is found by identifying points with large leverages and/or large residuals.

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Checking the model 2: Independent errors ?

Assumption no. 2: the errors should be independent, is mainly checked by considering how the data was collected.

The assumption is violated if

- some of the persons are relatives (and some are not) and the dependent variable have some genetic component.
- some of the persons were measured using one instrument and others with another.
- in general if the persons were sampled in clusters.

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Checking the model 3: Extending the model

One should **also** try to check the validity of the linearity assumption that is the assumption of **additivity**, **proportionality** and **no effect modification** (no interaction).

It can be done by:

1. Introducing an the explanatory variable in a **different scale**, e.g. adding age^2 or $\log(age)$
2. Introducing the explanatory variable as a **categorical** variable instead e.g. use age in divided into **agegroups** instead as age in years.
3. Introducing **interaction** between some of the explanatory variables.
4.