

Common mistakes in experimental design and analysis of pig trials: an overview.

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EAAP 2024
04-09-2024

ILVO

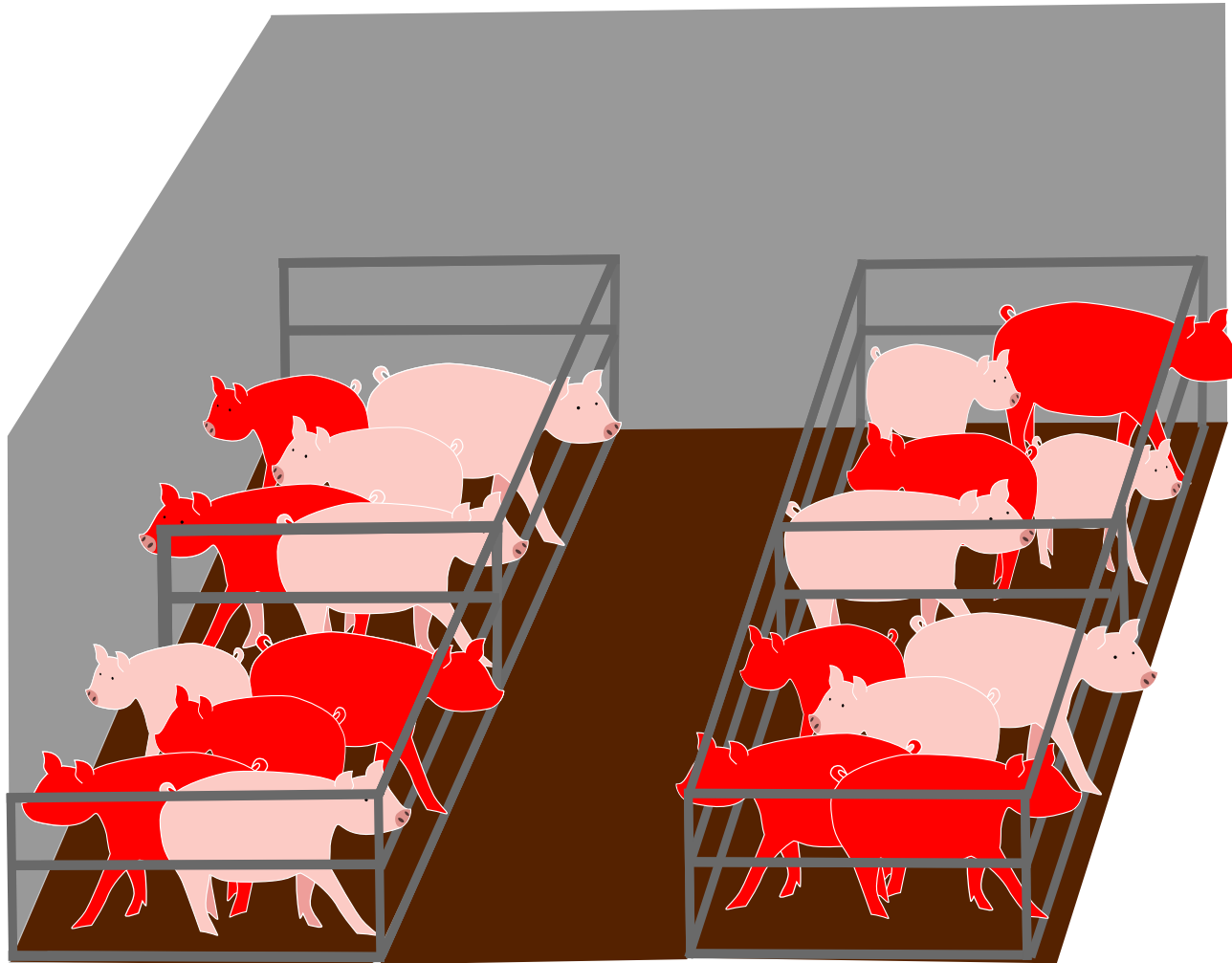
Outline

1. Design terminology
2. Blocking
3. Graphs vs Statistical analysis
4. Diagnostic plots
5. Different or equivalent
6. Interactions
7. Wrong interpretations

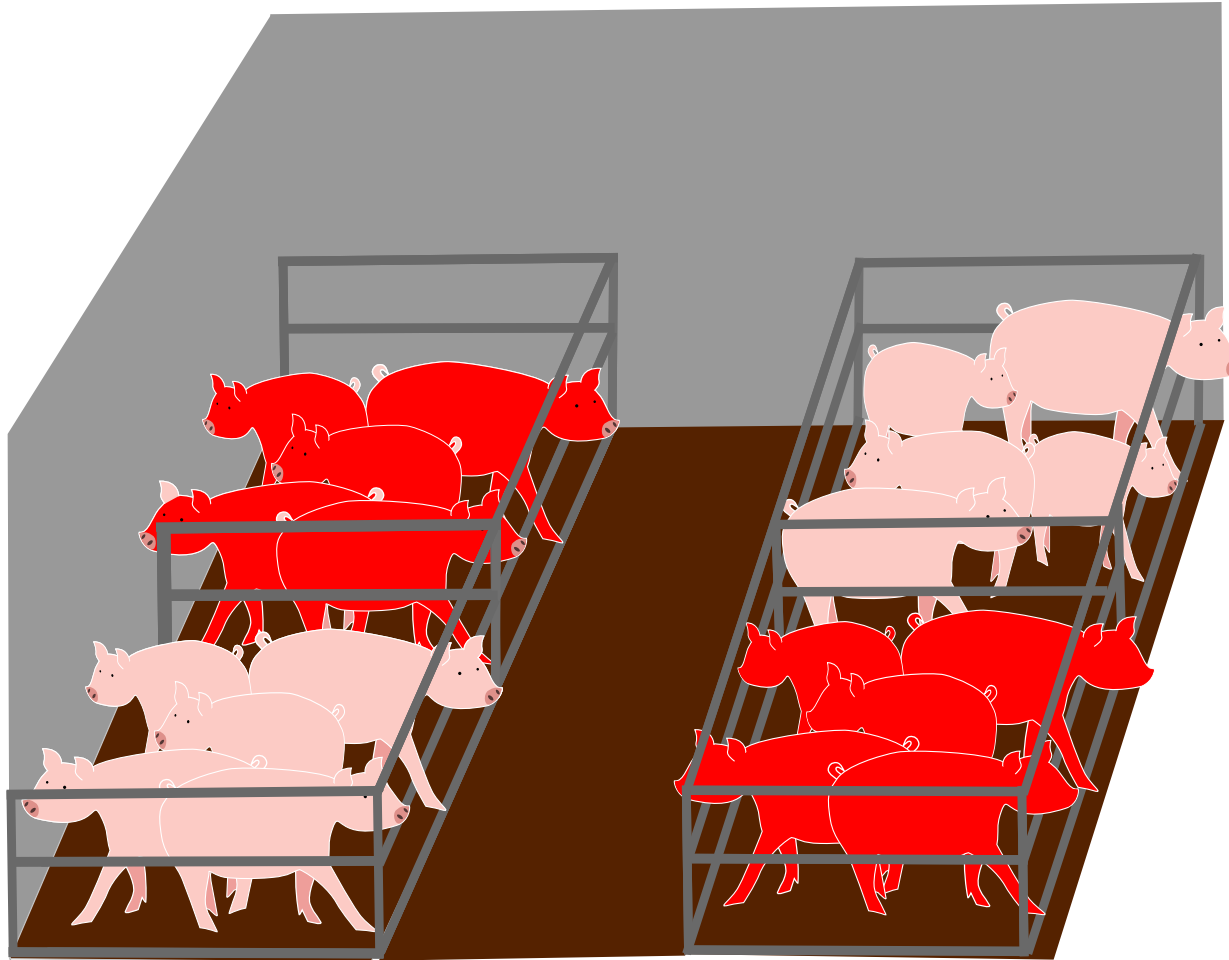
Experimental vs observational unit

- Experimental unit: The unit to which the treatment is randomly applied.
- Observational unit: The unit on which the response is measured

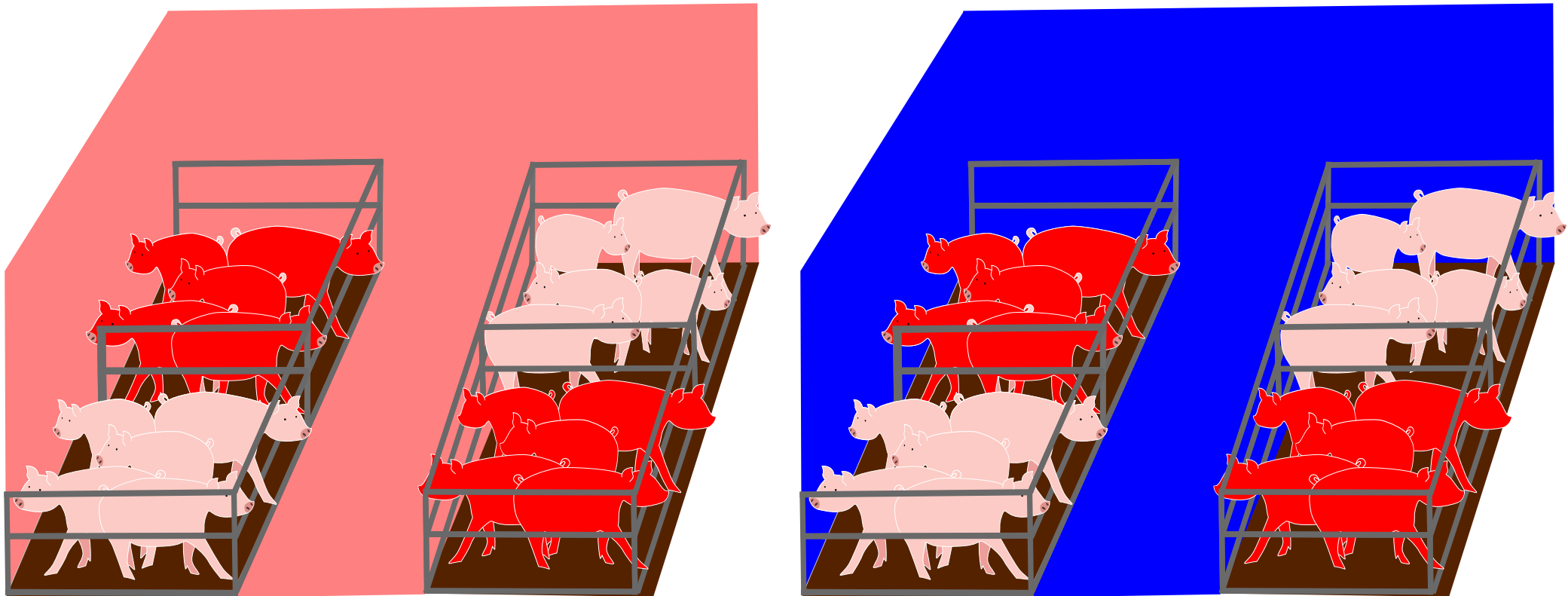
Experimental vs observational unit: example 1



Experimental vs observational unit: example 2



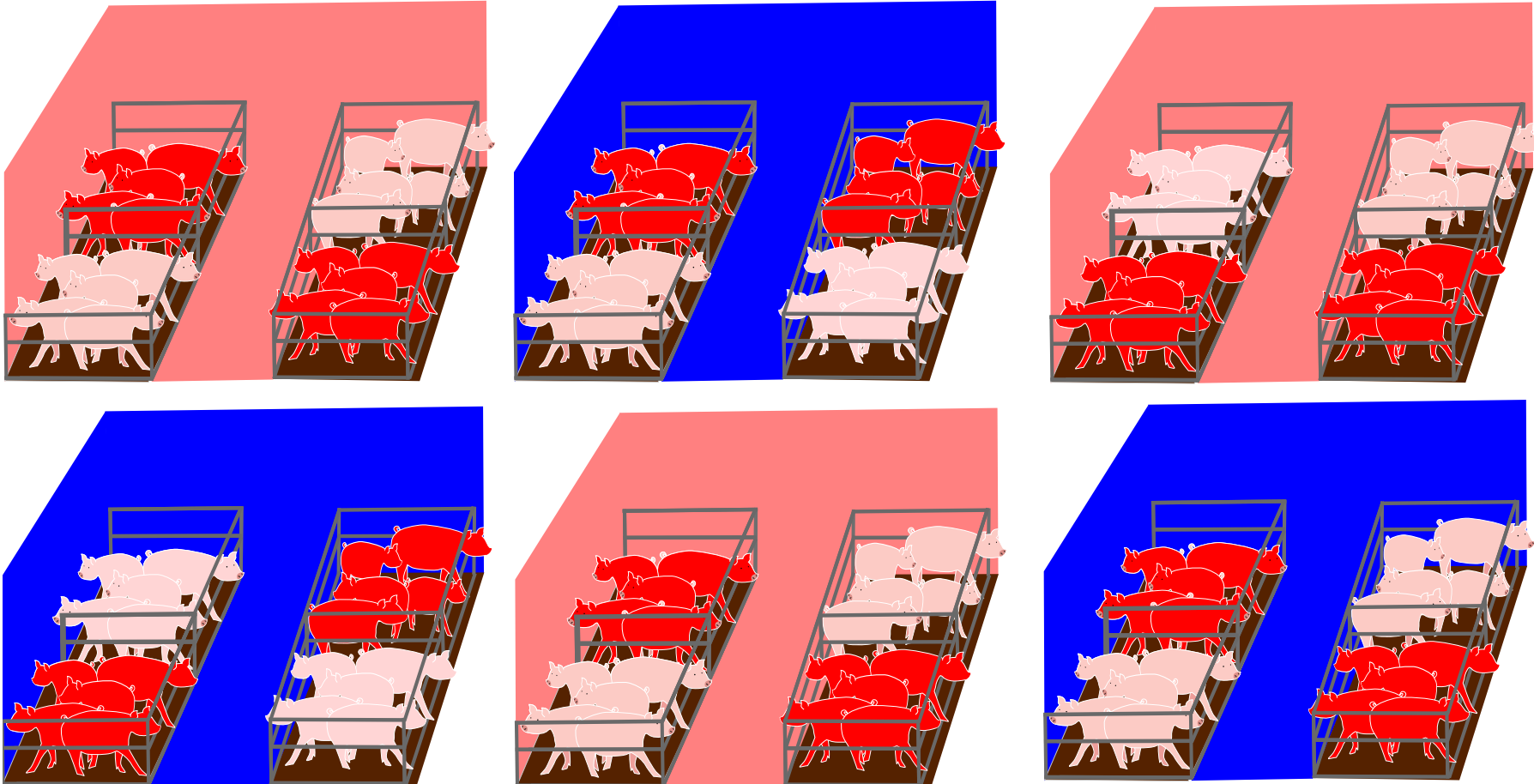
Experimental vs observational unit: example 3



replicate vs repeated measurement

- **Replication** involves running the same study on **different** subjects, independently but under identical conditions
- **Repeated** measures involves measuring the **same** subjects multiple times

A heatstress example:



“To call in the statistician after the experiment is done may be no more than asking him to perform a postmortem examination, he may be able to say what the experiment died of.”

R.A. Fisher, Indian Statistical Congress, Sankhya, ca 1938

An example of an experiment AB

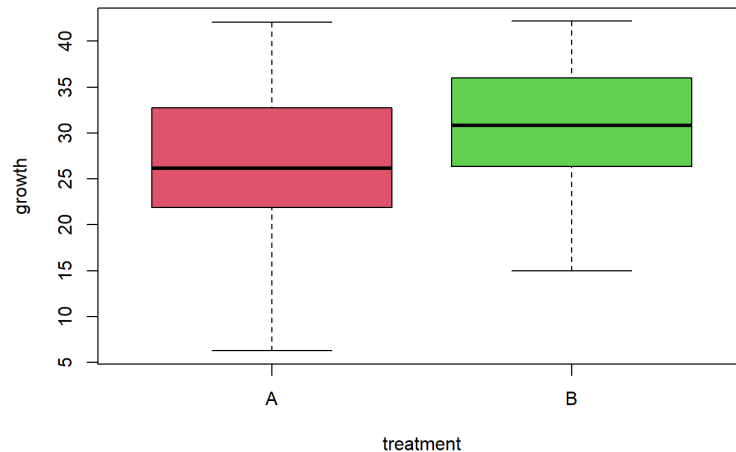
- Test the difference in growth of **food A vs B**
- Weight at start and end: **growth of each animal**
- **24 pens** available, 5 animals/pen = **120 animals**
- Pens blocked according to start weight: **low, mean and high** (8 pens each)
- Within each weight group: **randomization** for treatment on **pen-level** (balanced)

Analysis experiment AB (1)

- Simple linear model (ANOVA):

Call:

```
lm(formula = growth ~ treatment, data = data)
```



Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	26.1645	0.9414	27.794	< 2e-16
treatmentB	4.7095	1.3313	3.537	0.000579

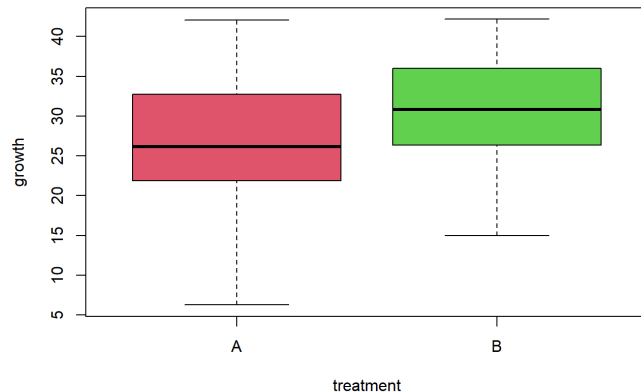
Residual standard error: 7.292 on 118 degrees of freedom

Multiple R-squared: 0.09588, Adjusted R-squared: 0.08822

F-statistic: 12.51 on 1 and 118 DF, p-value: 0.0005786

Analysis experiment AB (2)

• Simple linear model (ANOVA):



Anova Table (Type III tests)

Response: growth

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	41075	1	772.481	< 2.2e-16	***
treatment	665	1	12.513	0.0005786	***
Residuals	6274	118			

Simple linear model (ANOVA) on **pen-means**:

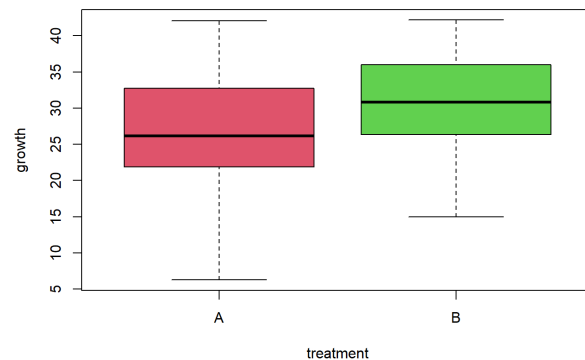
Anova Table (Type III tests)

Response: growth

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	8215.0	1	181.741	4.123e-12	***
treatment	133.1	1	2.944	0.1002	
Residuals	994.4	22			

Analysis experiment AB (3)

• Simple linear model (ANOVA):



Anova Table (Type III tests)

Response: growth

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	41075	1	772.481	< 2.2e-16	***
treatment	665	1	12.513	0.0005786	***
Residuals	6274	118			

linear MIXED model (ANOVA) **pen included as random:**

Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)

Response: growth

	F	Df	Df.res	Pr(>F)	
(Intercept)	181.741	1	22	4.123e-12	***
treatment	2.944	1	22	0.1002	

Conclusion:

NEVER IGNORE DESIGN:

**Analysis on level of
experimental unit!**

Analysis experiment AB (4)

linear MIXED model **pen included as random:**

Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)

Response: growth

	F	Df	Df.res	Pr(>F)	
(Intercept)	181.741	1	22	4.123e-12	***
treatment	2.944	1	22	0.1002	

linear MIXED model **pen included as random and weight group (block):**

Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)

Response: growth

	F	Df	Df.res	Pr(>F)	
(Intercept)	108.1645	1	20	1.629e-09	***
treatment	5.7537	1	20	0.0263211	*
block	11.4981	2	20	0.0004742	***

Conclusion:

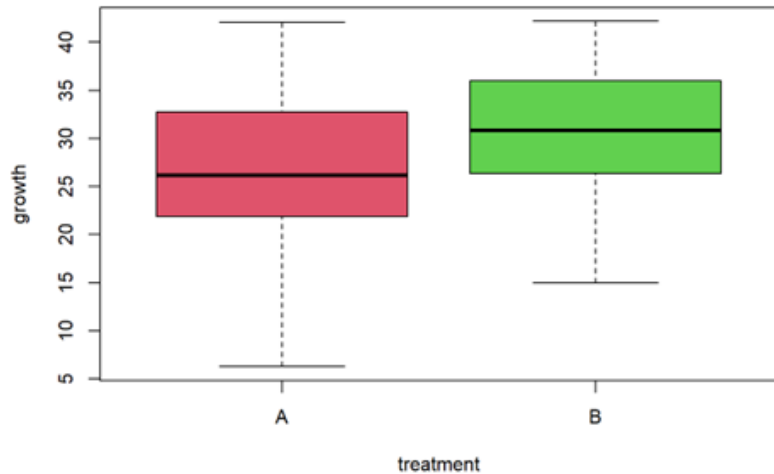
NEVER IGNORE DESIGN:

In case of blocking:

include block in your model!

Analysis experiment AB (4b)

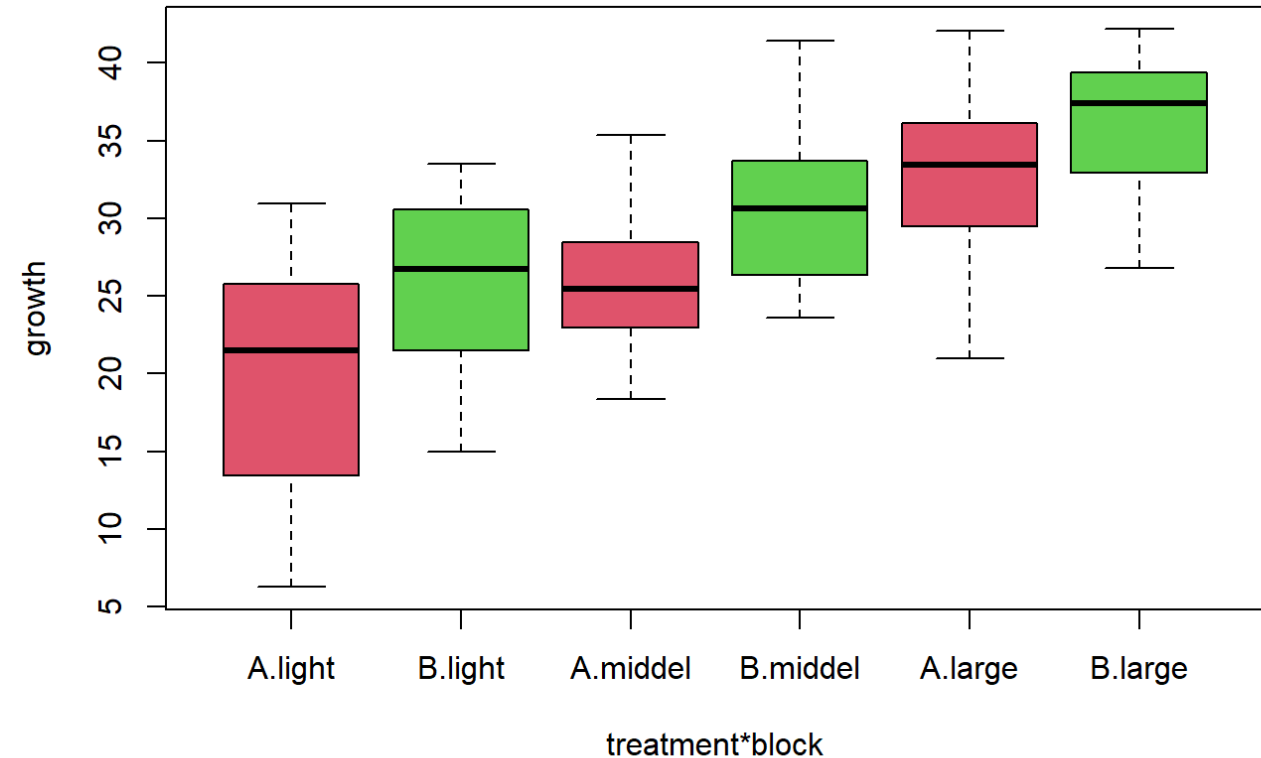
weight group included:



Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)

Response: growth

	F	Df	Df.res	Pr(>F)
(Intercept)	108.1645	1	20	1.629e-09
treatment	5.7537	1	20	0.0263211
block	11.4981	2	20	0.0004742



“Block what you can and
randomize what you
cannot.”

Box, Hunter and Hunter 1978

Another Example analysis: dataset

A		B		C		D	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

Adapted from Anscombe, Francis J. (1973). Graphs in statistical analysis. *The American Statistician*, **27**, 17–21. doi: 10.2307/2682899.

Summary statistics

A		B		C		D	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

Variable: X

	mean	sd	n
A	9	3.316625	11
B	9	3.316625	11
C	9	3.316625	11
D	9	3.316625	11

Variable: Y

	mean	sd	n
A	7.500909	2.031568	11
B	7.500909	2.031657	11
C	7.500000	2.030424	11
D	7.500909	2.030579	11

Linear regression...

A		B		C		D	
x	y	x	y	x	y	x	y
10.0	8.04	10.0	9.14	10.0	7.46	8.0	6.58
8.0	6.95	8.0	8.14	8.0	6.77	8.0	5.76
13.0	7.58	13.0	8.74	13.0	12.74	8.0	7.71
9.0	8.81	9.0	8.77	9.0	7.11	8.0	8.84
11.0	8.33	11.0	9.26	11.0	7.81	8.0	8.47
14.0	9.96	14.0	8.10	14.0	8.84	8.0	7.04
6.0	7.24	6.0	6.13	6.0	6.08	8.0	5.25
4.0	4.26	4.0	3.10	4.0	5.39	19.0	12.50
12.0	10.84	12.0	9.13	12.0	8.15	8.0	5.56
7.0	4.82	7.0	7.26	7.0	6.42	8.0	7.91
5.0	5.68	5.0	4.74	5.0	5.73	8.0	6.89

Call:

```
lm(formula = Y ~ X, data = data)
```

Coefficients:

	Estimate	s.e	t value	Pr(> t)	
(Intercept)	3.00	1.12	2.667	0.025	*
X	0.50	0.11	4.239	0.002	**

Residual standard error: 1.237 on 9 degrees of freedom

Multiple R-squared: 0.6662,

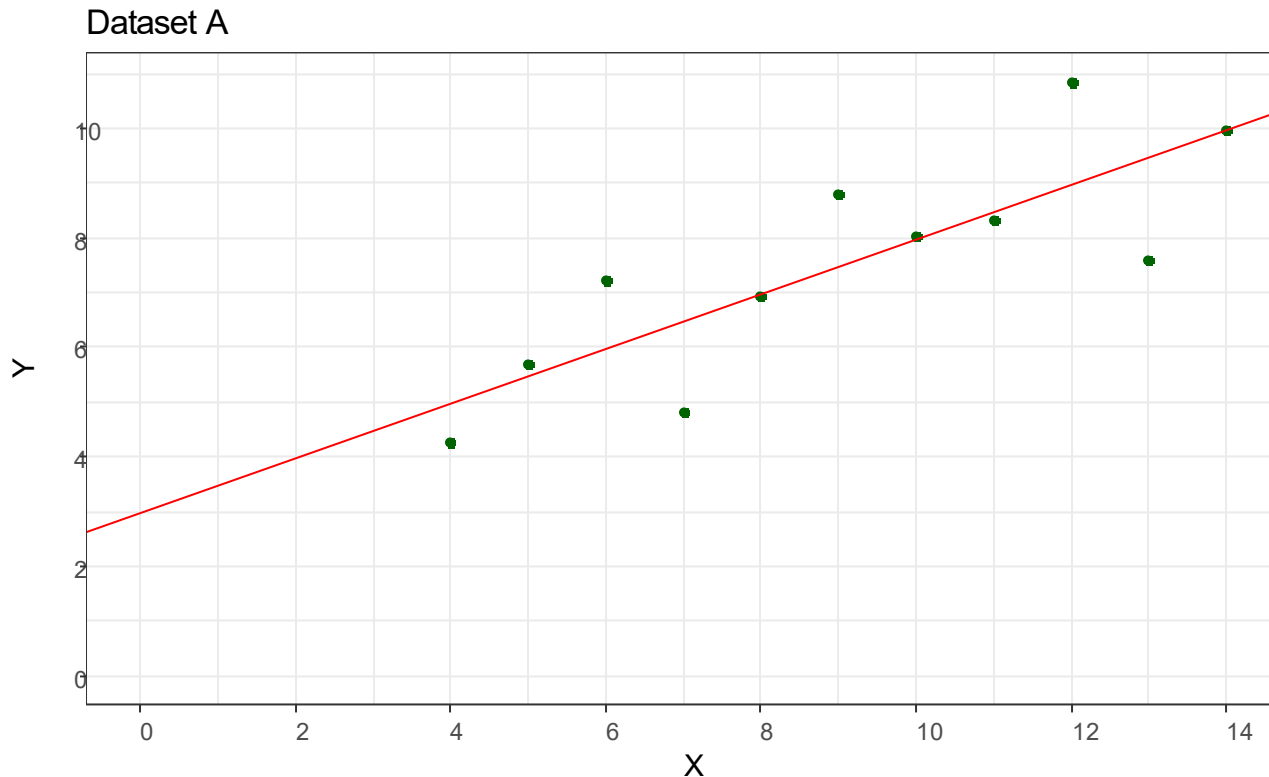
Adjusted R-squared: 0.6292

F-statistic: 17.97 on 1 and 9 DF,

p-value: 0.002179

Let's compare the results with the data:

Dataset A



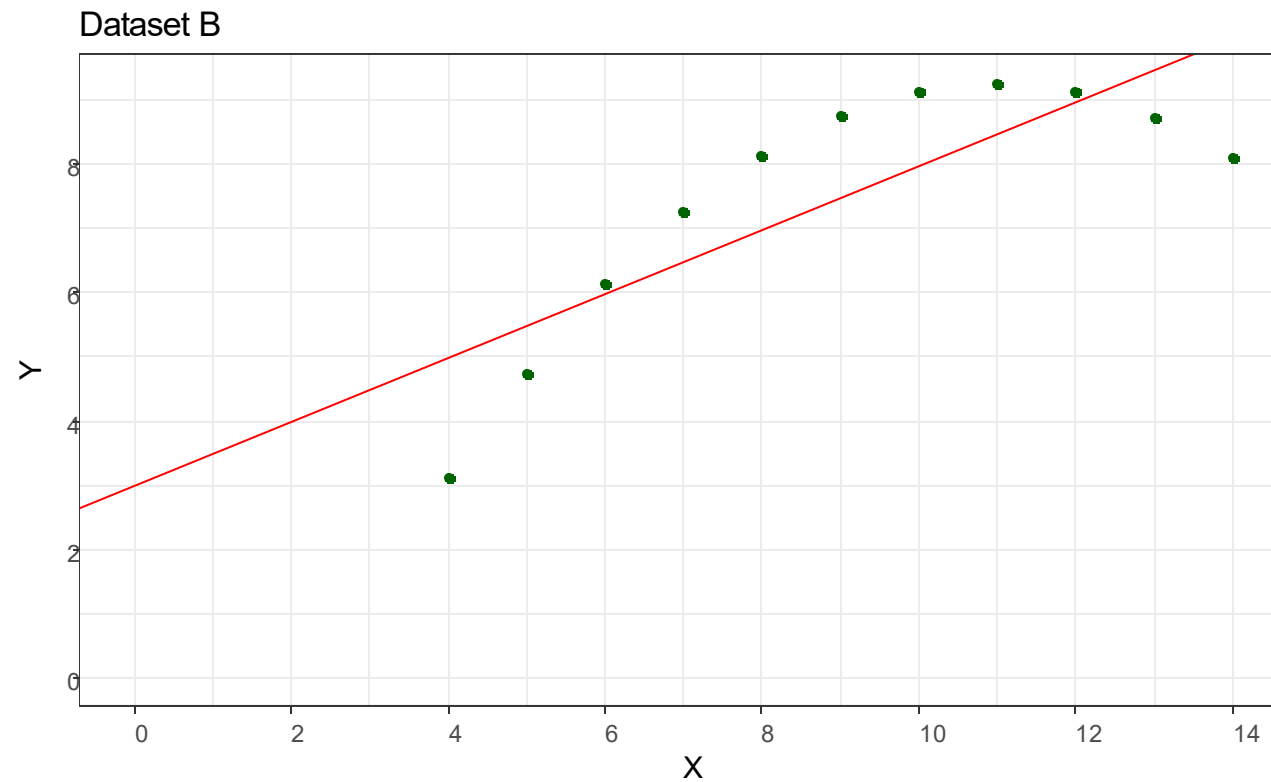
Call:
`lm(formula = Y ~ X)`

Coefficients:

	Estimate	s.e
(Intercept)	3.00	1.12
X	0.50	0.11

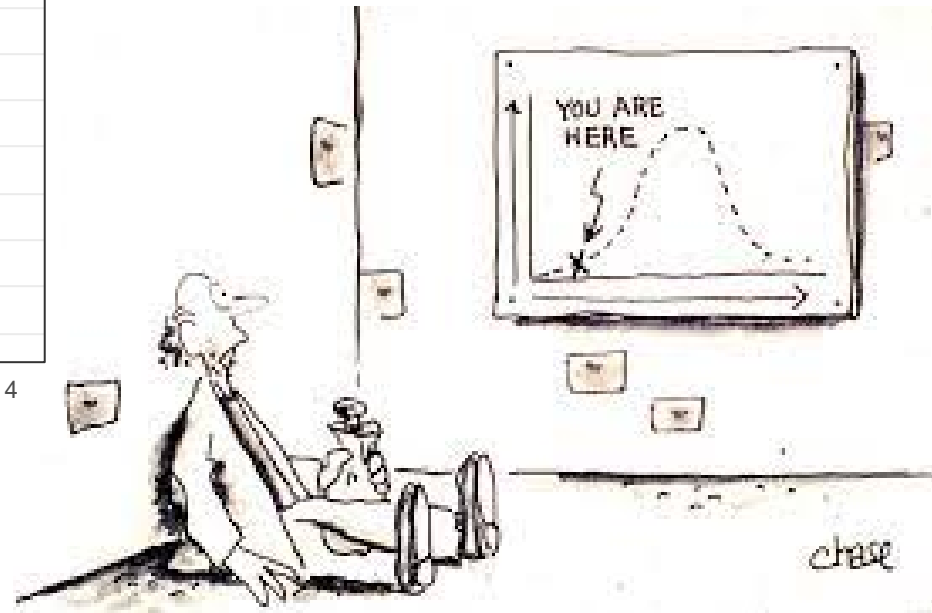
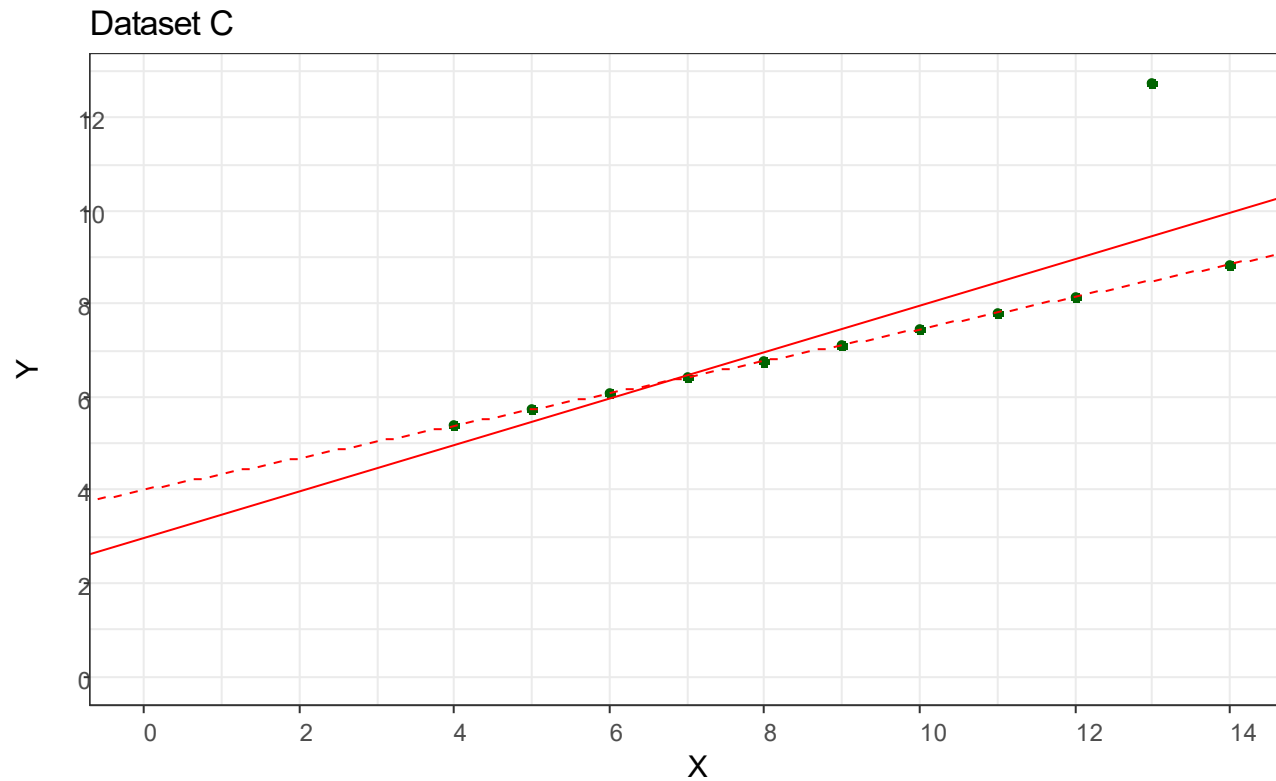
Let's compare the results with the data:

Dataset B



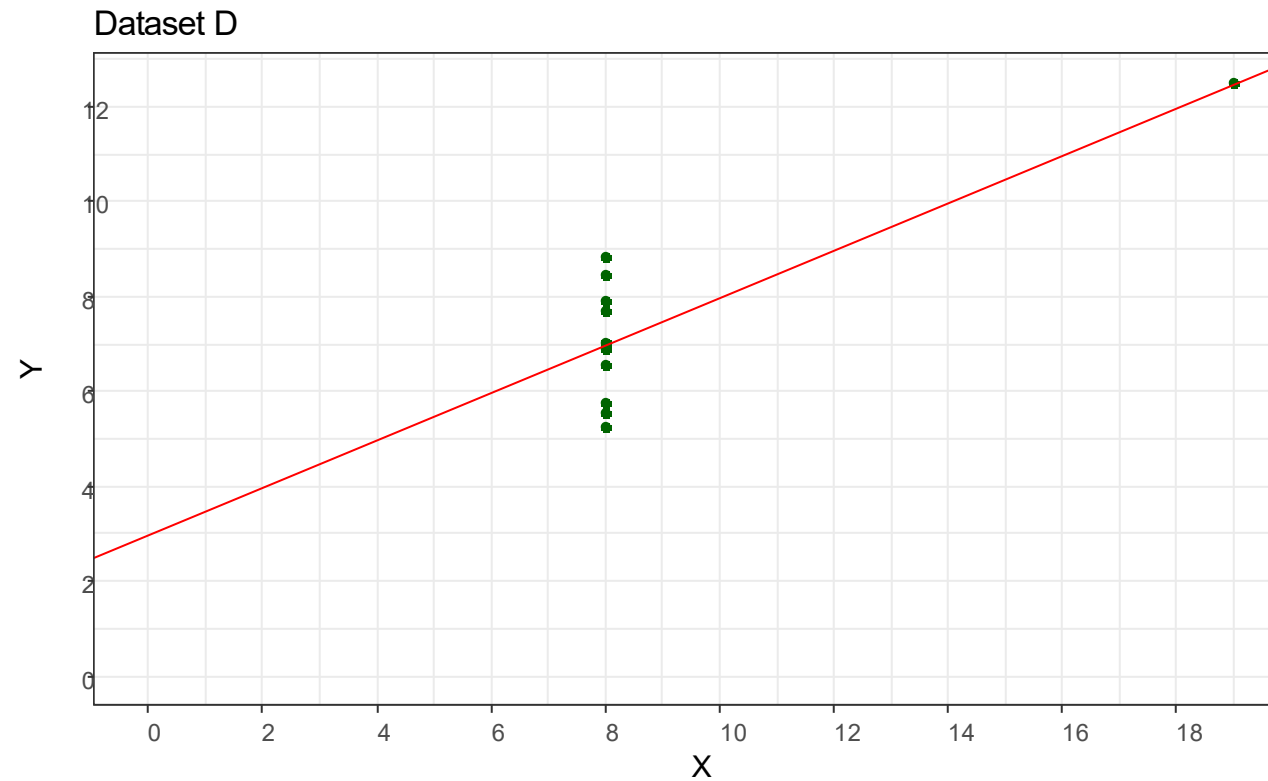
Let's compare the results with the data:

Dataset C

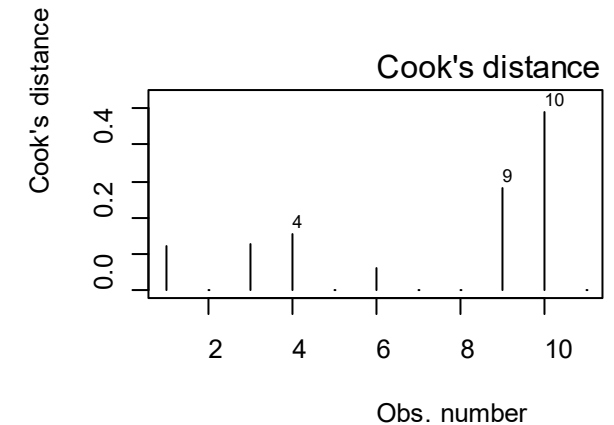
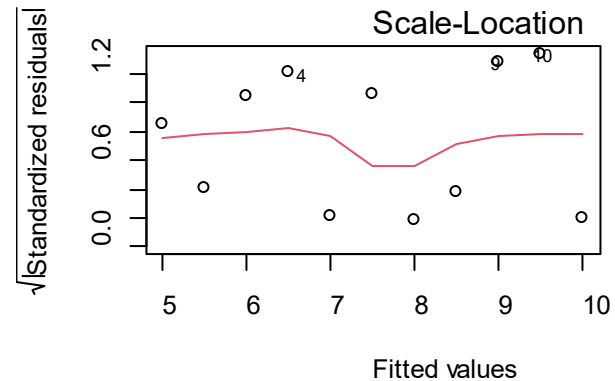
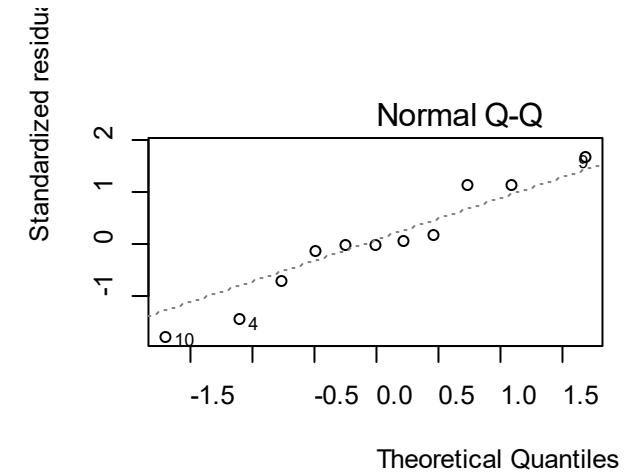
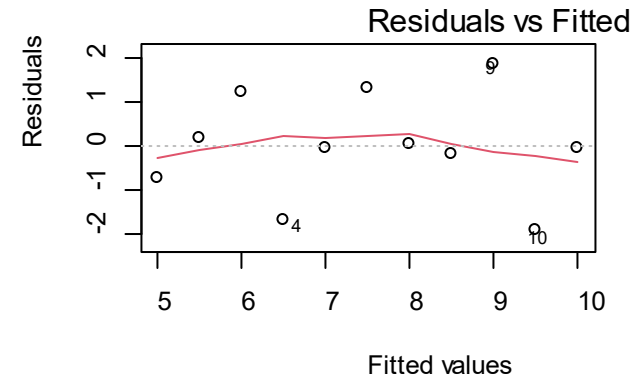
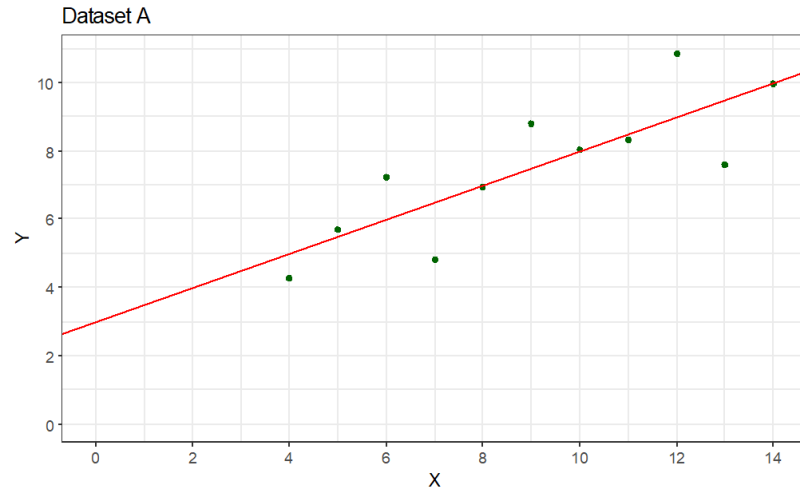


Let's compare the results with the data:

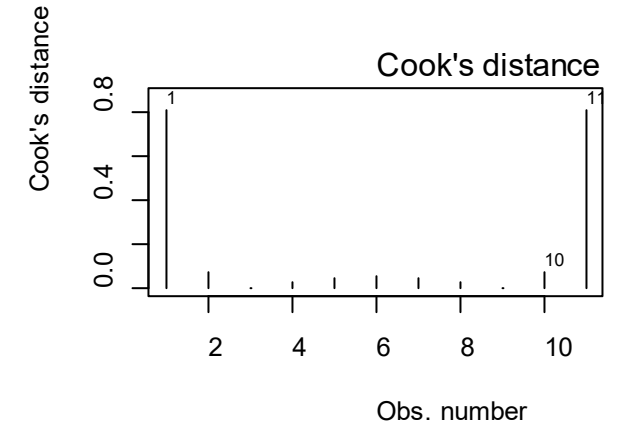
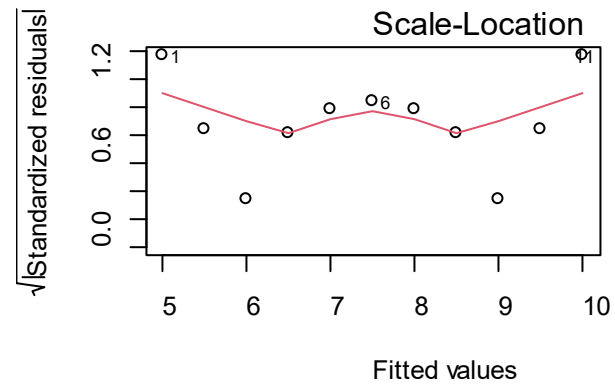
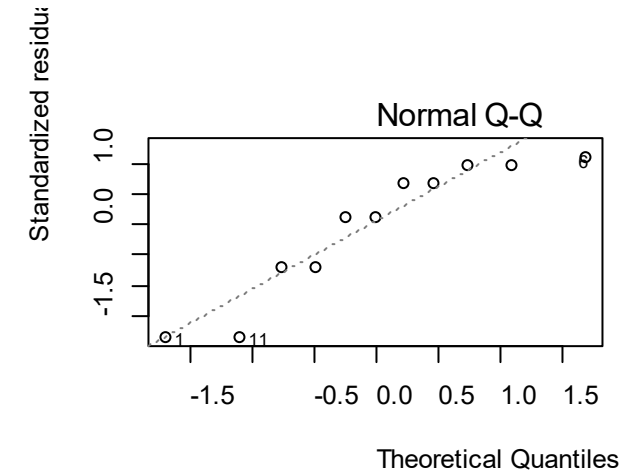
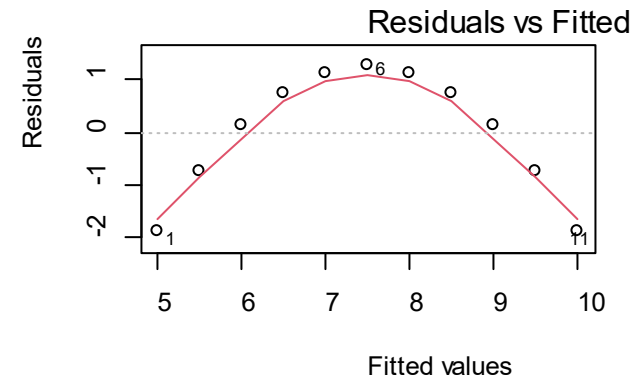
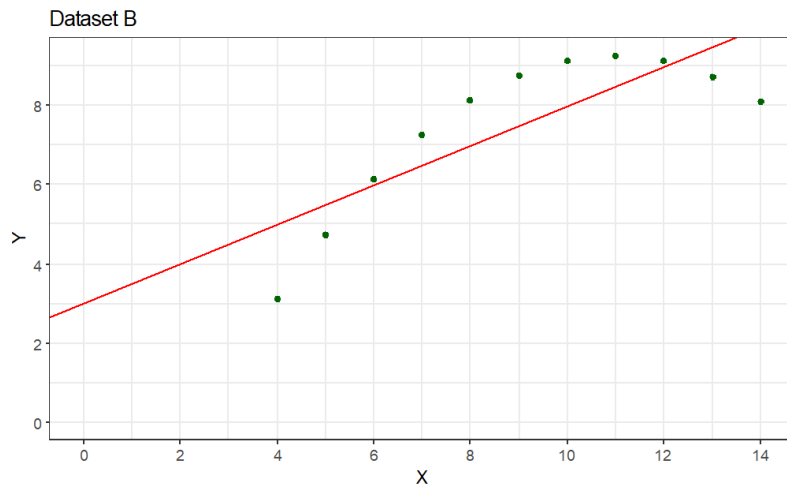
Dataset D



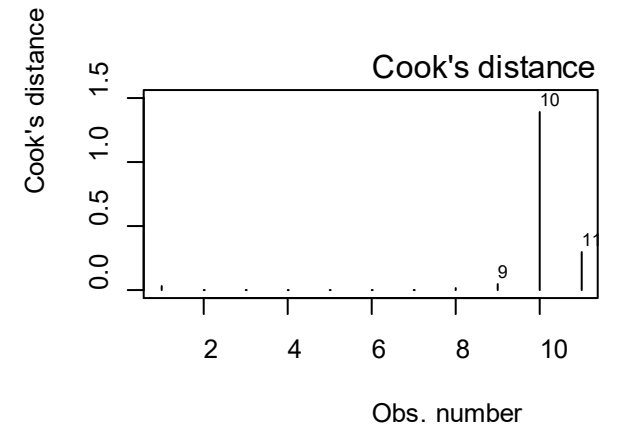
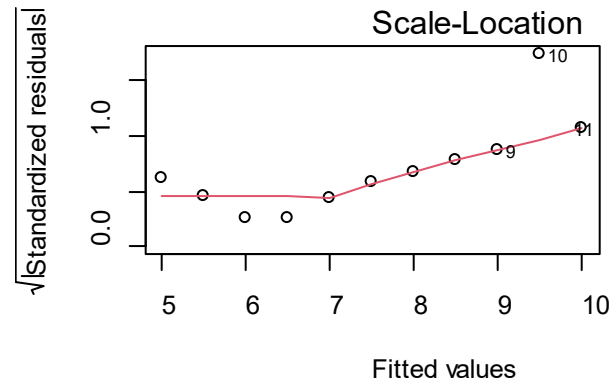
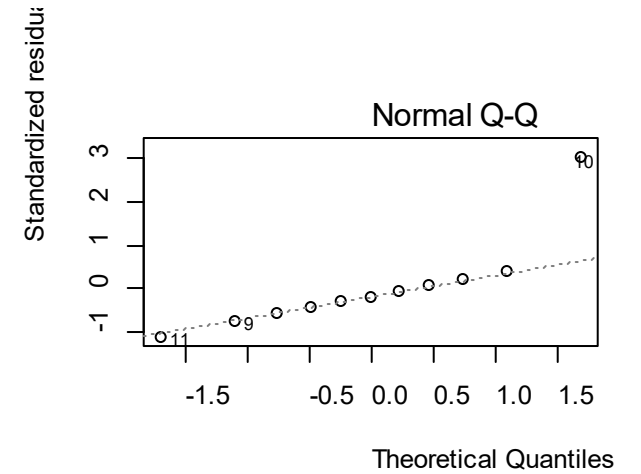
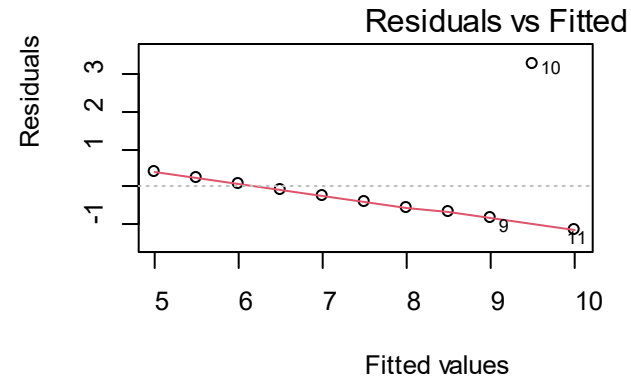
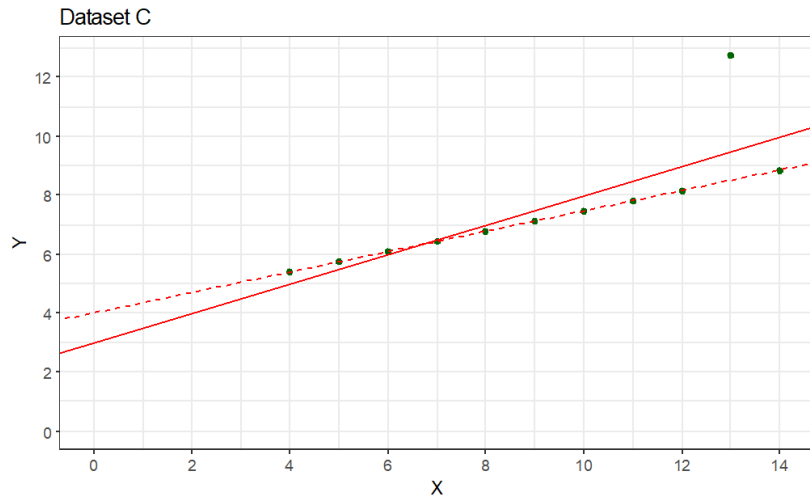
Let's inspect diagnostic plots: Dataset A



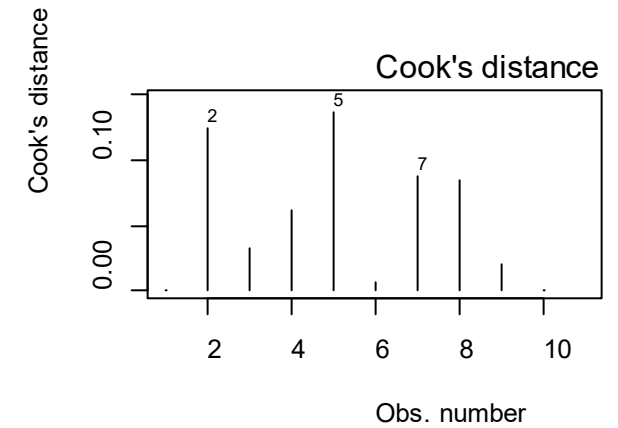
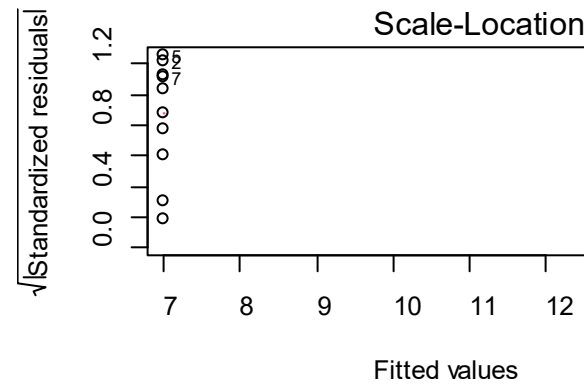
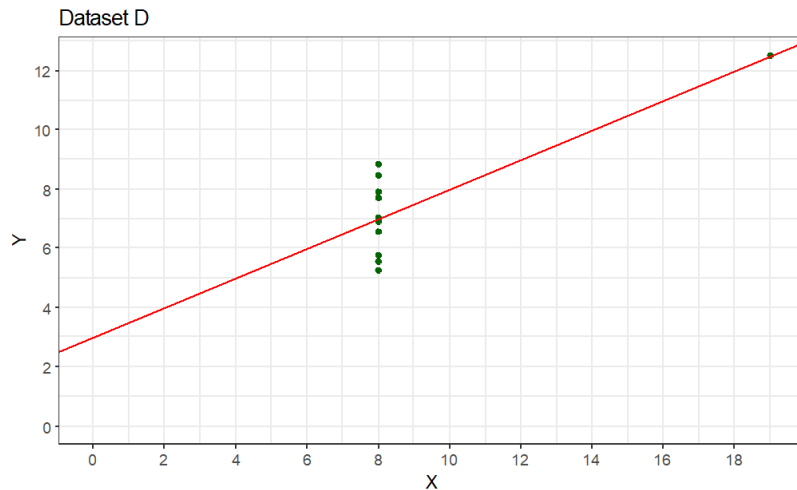
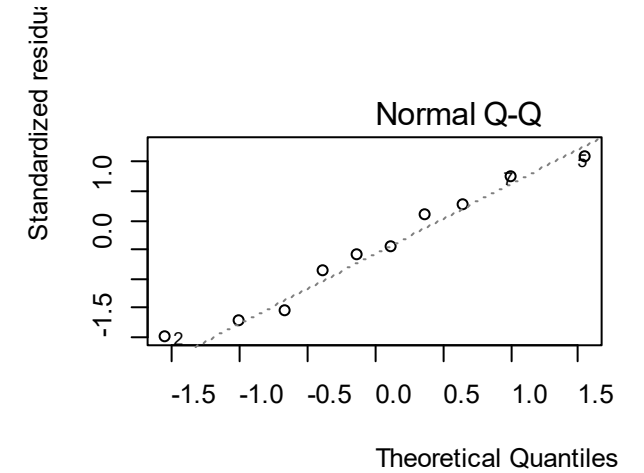
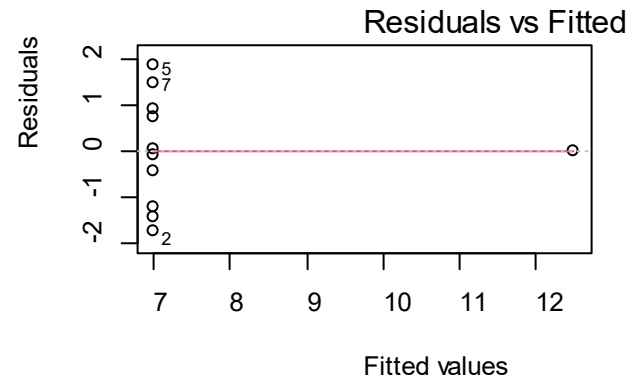
Let's inspect diagnostic plots: Dataset B



Let's inspect diagnostic plots: Dataset C



Let's inspect diagnostic plots: Dataset D

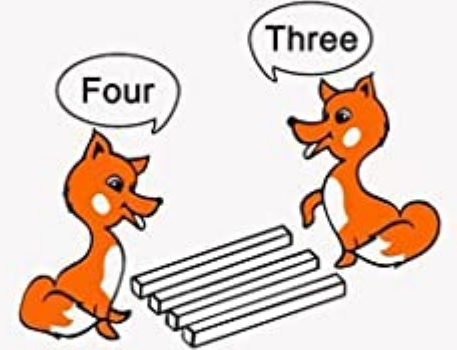


Graphs: Conclusion

- Always create graphs to see if your model describes the data.
- A model can give a perfect fit but still be non-sense.
- Using diagnostic graphs can help you detect inappropriate models

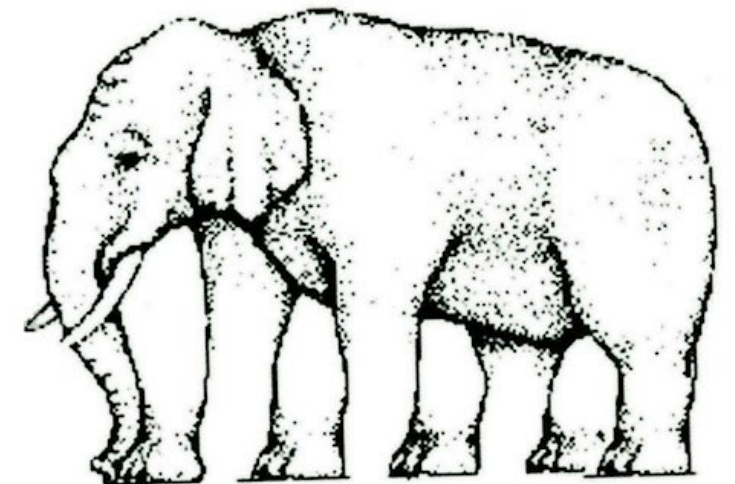
Papillae Piglets (fictitious example)

- Skin tone is determined by the number of papillae:
 - Determination: Manually count on histological slice
 - New technique: Image analysis via machine-learning
- Objective research: Compare the two techniques, can the new technique replace manual counts?



Papillae Piglets: design 1

- Experimental design:
 - 5 histological slices: each manual count and AI count
- Analysis:
 - Paired t-test
- Results:
 - P-value: 0.20 -> no significant difference
- Conclusion:
 - The two techniques are the same!



Papillae Piglets: design 2

- Experimental design:
 - 14 histological slices: each manual count and AI count
- Analysis:
 - Paired t-test
- Results:
 - P-value: 0.0453 -> significant difference
- Conclusion:
 - The two techniques are different!

Papillae piglets: overall conclusion?

- Where is the reasoning error??
 - The research question was actually whether the two techniques are the same...
 - But: statistical test for difference
 - No significant difference does not mean that they are equal!



Papillae Piglest: equivalence test?

- Solution: equivalence testing!
 - First determine equivalence limits: In this case, experts determined that this is 100 (on an average of ± 1000)
 - Determine if CI for the difference is within the equivalence limits

Papillae Piglets: output R

Paired t-test data:

Mar_Mir_pair\$GemA.A[1:5] and Mar_Mir_pair\$GemA.B[1:5]

t = 1.5406, df = **4**, p-value = **0.1983**

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

-61.2744 214.0424

sample estimates: mean of the differences

76.384

Paired t-test data:

Mar_Mir_pair\$GemA.A and Mar_Mir_pair\$GemA.B

t = 2.2142, df = **13**, p-value = **0.0453**

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

1.135941 92.304059

sample estimates: mean of the differences

46.72



"I can prove it or disprove it! What do you want me to do?"

Papillae Piglets: equivalence test

- Design: 5 histological slices:
 - 95% CI for the difference:
[-61.3 ; 214.0]
 - Conclusion: the two techniques may not be considered equivalent
- Design: 14 histological slices:
 - 95% CI for the difference:
[1.1 ; 92.3]
 - Conclusion: both techniques are considered to be equivalent (difference is less than 100).

Papillae piglets: equivalence

- Design: 14 histological slices
- Analyse: equivalence test
- Results:
 - Manual: 1059 (sd 79)
 - Machine learning: 1012 (sd 67)
- 95% CI for the difference:
[1.1 ; 92.3]
- Conclusion: both techniques are considered to be equivalent (difference is less than 100).

Equivalence test: Conclusion

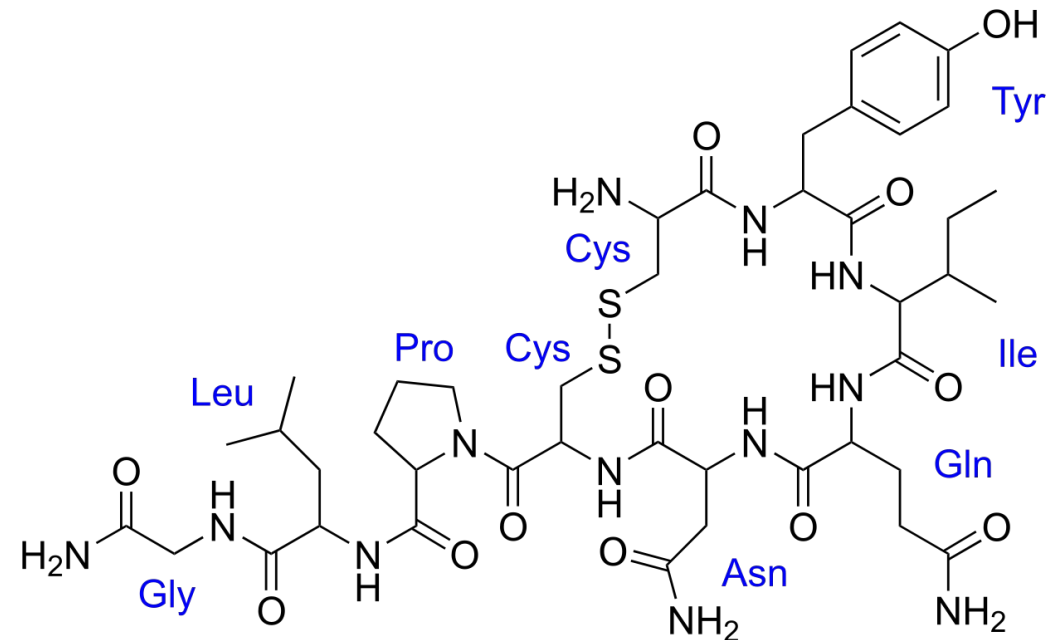
- Absence of a significant difference does not mean that two groups are equal (power may be too low)
- Equivalence can be tested with an equivalence test (usually many observations required) with predefined equivalence limits.
- Two groups can be significant different and yet equivalent (over-powered with an irrelevant difference)

The effect of experimental hormone OXY on the growth of piglets and the high risk of interactions with the environment (fictitious example)

a critical look at the misuse/misinterpretation of
linear models with interactions

Hormone OXY

- Action in mammals:
 - Experimental growth-like hormone.
 - Does it work or not in piglets?

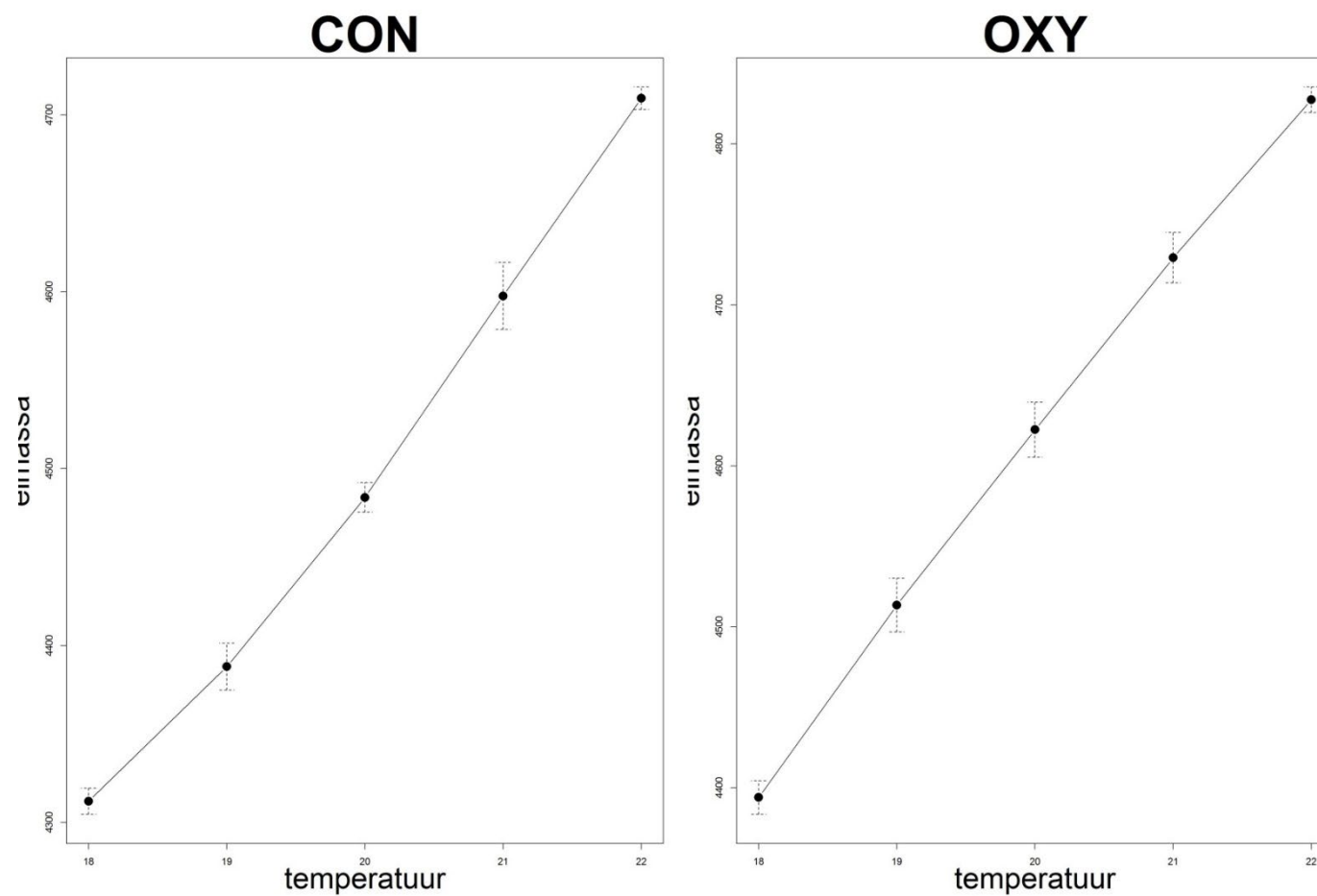


Hormone OXY

- Research question:
 - Has hormone OXY a positive effect on the growth of piglets
- Experimental design:
 - 40 piglet pairs ad random assigned to OXY or control group:
 - 5 environmental temperatures: 18, 19, 20, 21, 22°C
 - Separate housing and temperature control for each piglet pair
 - Total growth (g) during predefined period

Hormone OXY

- Results:



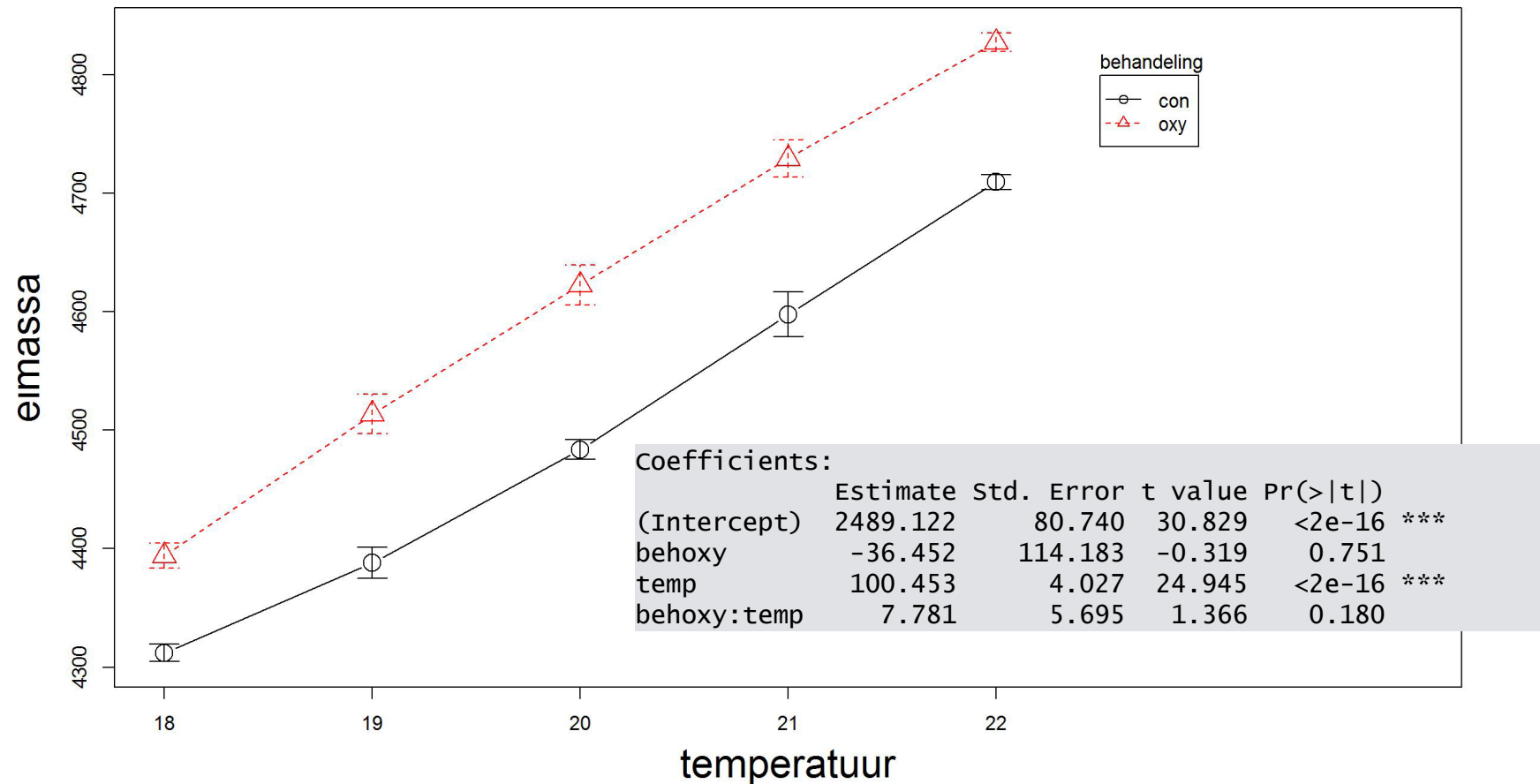
Hormone OXY

- Results:
 - Temp significant ($p < 0,001$)
 - Effect hormone OXY not significant ($p = 0,75$)
 - Interaction Temp: OXY not significant ($p = 0,18$)
- Conclusion:
 - Hormone OXY does not improve the growth of piglets.

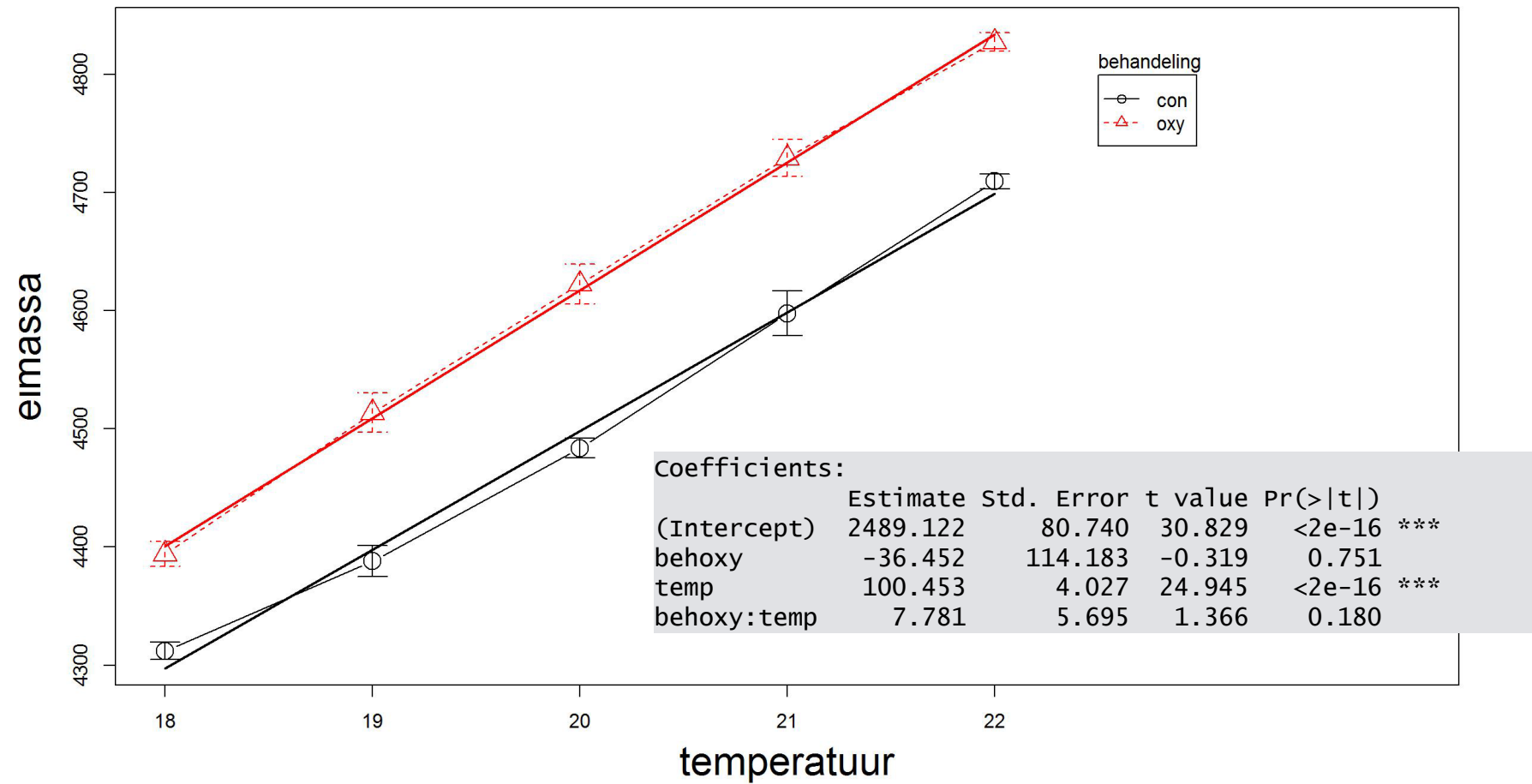
Critical look at the analyzes?

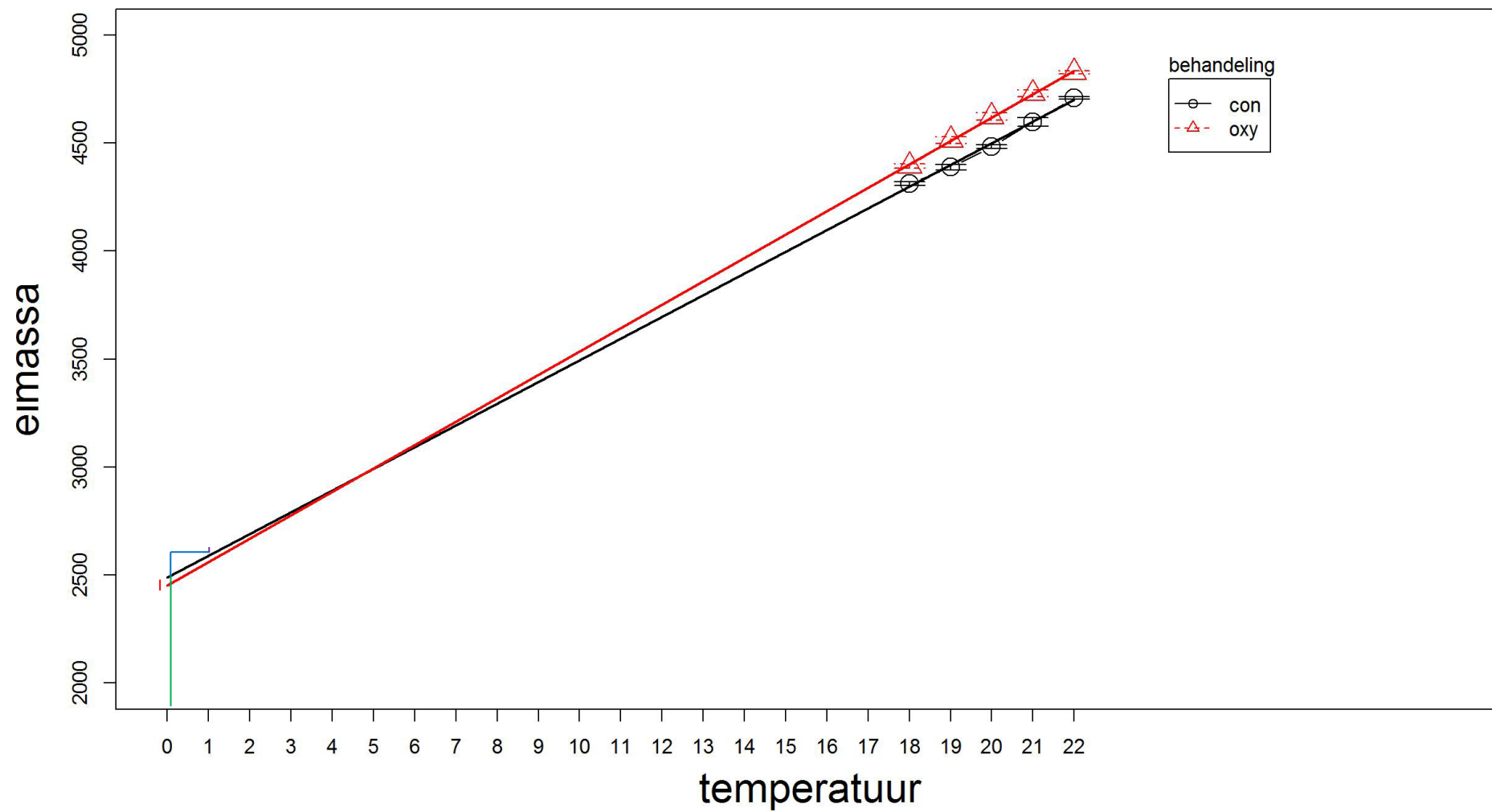
The conclusion was wrong!

Hormone OXY: graph



Hormone OXY: graph



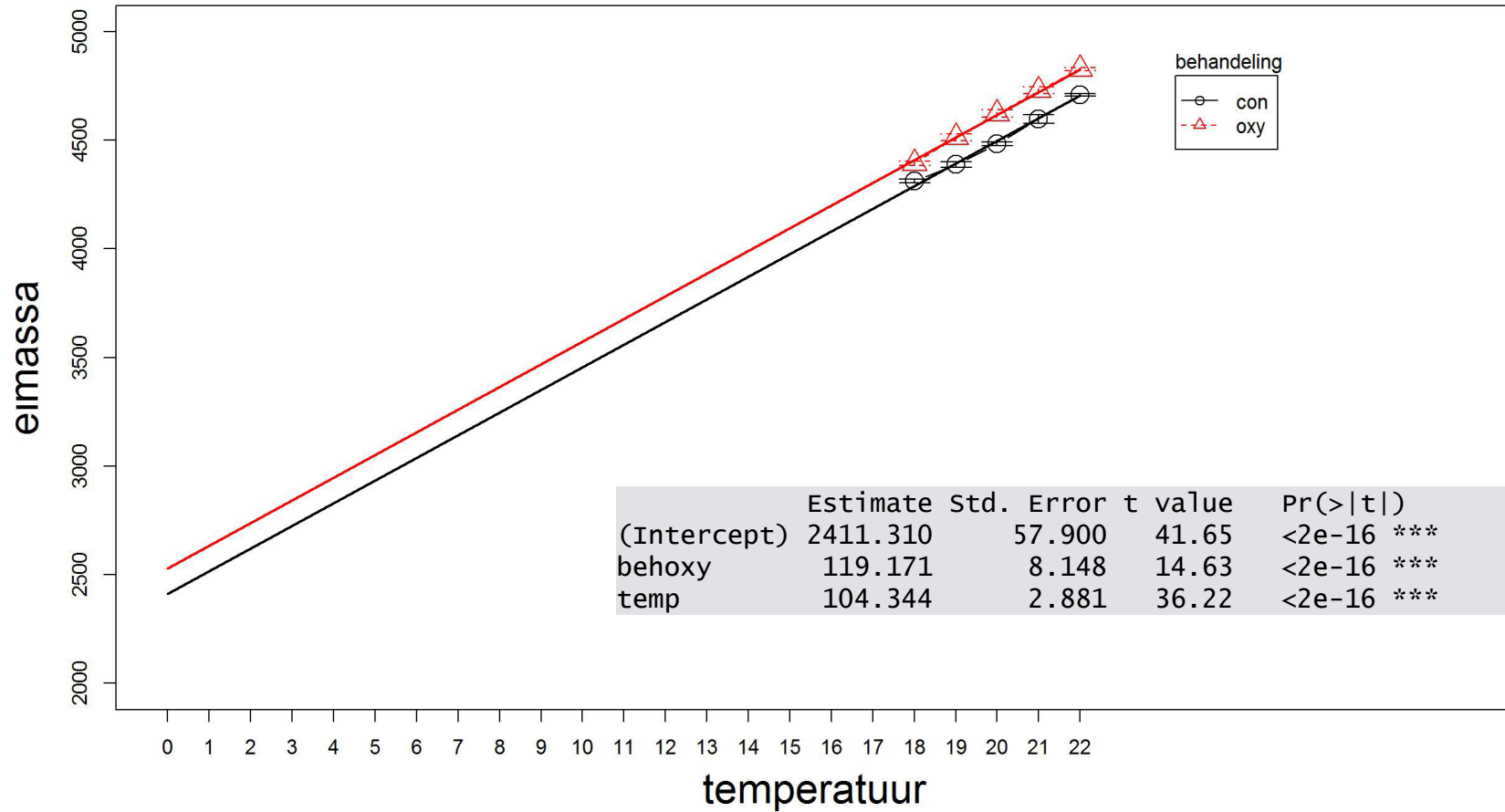


Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2489.122	80.740	30.829	<2e-16 ***
behoxy	-36.452	114.183	-0.319	0.751
temp	100.453	4.027	24.945	<2e-16 ***
behoxy:temp	7.781	5.695	1.366	0.180

growth=Intercept+temp+treat+treat*temp

OXY: only main effects (no interaction)



Hormone OXY: only main effects

- Results:
 - Positive effect of temp ($p < 0,001$)
 - Positive effect hormone OXY ($p < 0,001$)
- Conclusion:
 - Hormone OXY has a positive effect on the growth of piglets!!!

Main conclusion:

- If an interaction in the model:

**NEVER LOOK AT THE
MAIN EFFECTS
SEPARATELY**

Correlation vs Causation

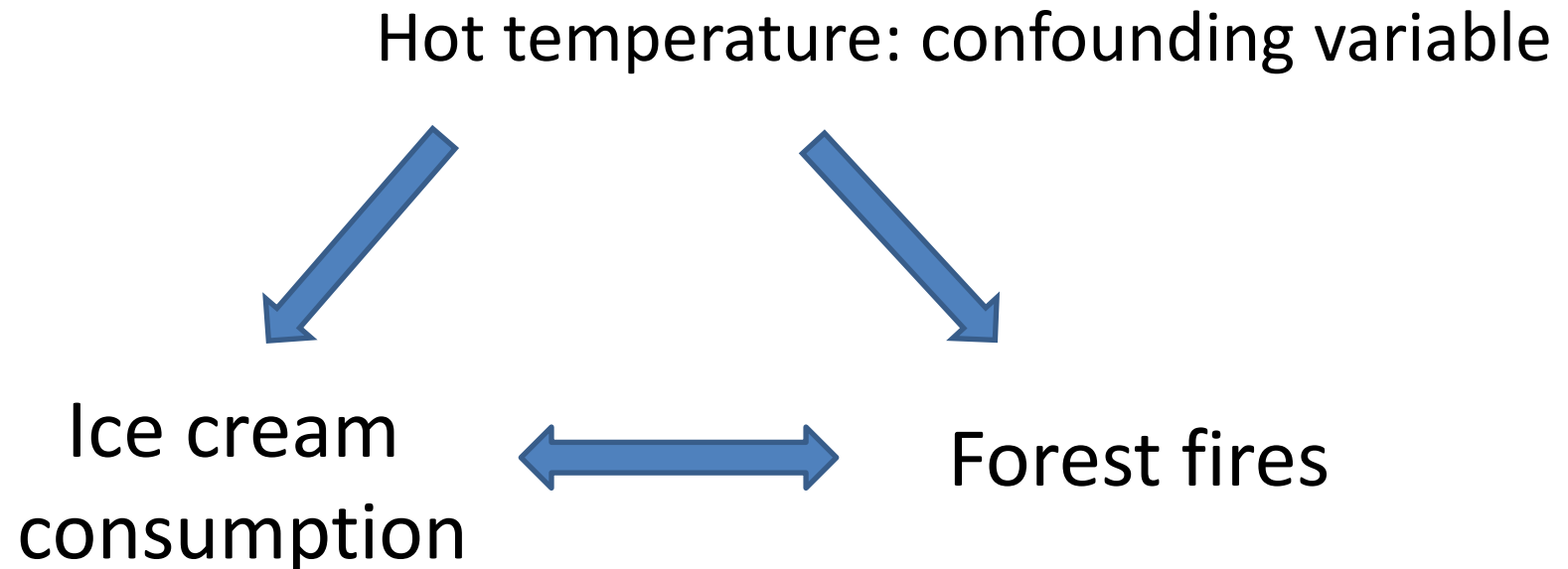
- Correlation: the amount of forest fires increases alongside an increase in people buying ice cream.
- Does this mean that people buying ice cream are causing the fires?

Observational vs Experimental

- Observational: the amount of forest fires increases alongside an increase in people buying ice cream. This is a correlation
- Experimental: force an increase in ice cream consumption in some regions and observe the number of fires compared to the control regions...

Confounding variable

- Correlation: the amount of forest fires increases alongside an increase in people buying ice cream.



A green frog is perched on a large, vibrant green leaf. The frog is facing towards the right side of the frame. The leaf has prominent veins and a slightly textured surface. The background is a soft-focus green, suggesting a natural outdoor setting.

**Scientists tested a frog.
They cut it's legs off and
said, "Jump!" The frog
didn't jump. Scientists
therefore concluded that
when frogs lose their legs
they become deaf.**

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Thanks to:

Everyone who did something wrong
in the past!

Questions?

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