

Kausale Effektschätzung - ANCOVA

Aufgabe 1: Datensatz und Deskriptivstatistiken

```
str(spf2)
```

```
'data.frame':  289 obs. of  3 variables:
 $ schule: Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
 $ HISEI : num  26.6 28.5 30.5 75.5 70.1 ...
 $ hoeren: num  226 252 439 413 573 ...
```

```
# Verteilung auf die Schulformen
table(spf2$schule)
```

```
0    1
77 212
```

```
# Unbedingter Mittelwert der Kompetenz `hören`
mean(spf2$ hoeren)
```

```
[1] 322.9552
```

```
# Gruppenspezifische Kompetenz-Werte
tapply(spf2$ hoeren, spf2$schule, mean)
```

```
0      1
263.8902 344.4081
```

```
# Gruppenspezifische Werte auf der Kovariate
tapply(spf2$HISEI, spf2$schule, mean)
```

```
0      1
35.68519 39.58231
```

Aufgabe 2: Prima Facie Effekt der Hörkompetenz

```
## t-Test
m1 <- lm(hoeren ~ schule, spf2)
summary(m1)$coef
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	263.89023	12.71918	20.747417	4.808921e-59
schule1	80.51785	14.85047	5.421905	1.252209e-07

$$\widehat{PFE} = 80.52$$

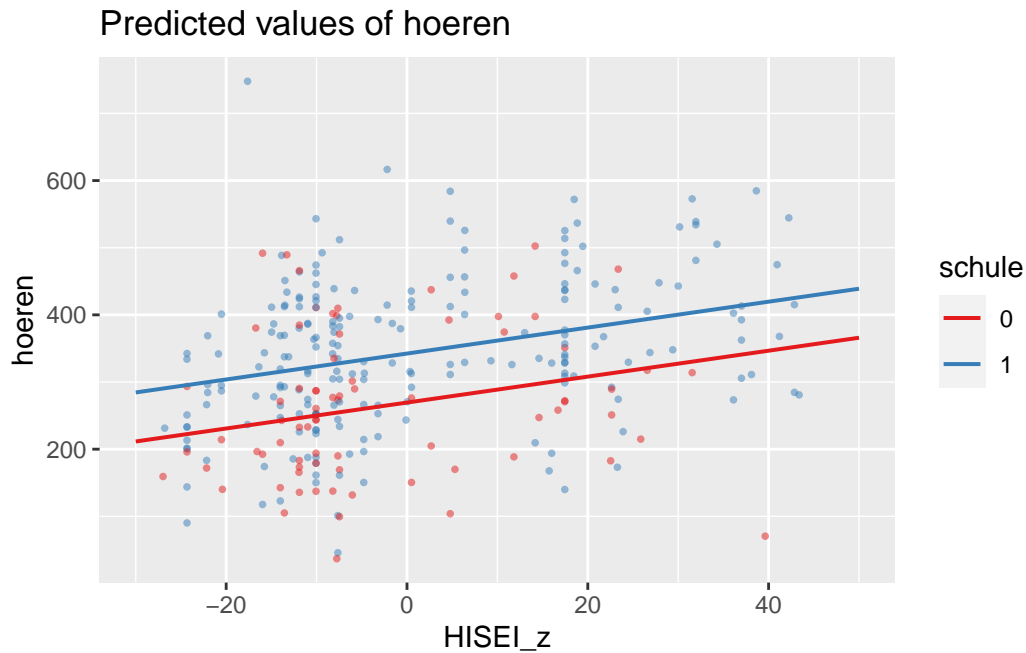
Aufgabe 3: Traditionelle ANCOVA

```
# Zentrierung der Kovariate am Gesamtmittelwert
library(jtools)
spf2$HISEI_z <- center(data = spf2$HISEI)
# trad. ANCOVA
m2 <- lm(hoeren ~ HISEI_z + schule, spf2)
summary(m2)$coef
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	269.409676	12.2070746	22.069962	1.039432e-63
HISEI_z	1.930697	0.3656082	5.280781	2.550353e-07
schule1	72.993695	14.2715132	5.114643	5.768561e-07

Aufgabe 4: Streudiagramm

```
library(sjPlot)
plot_model(m2, type = "pred",
           terms = c("HISEI_z", "schule"),
           show.data = TRUE, dot.size = 1, # graph. Parameter
           ci.lvl = NA)
```



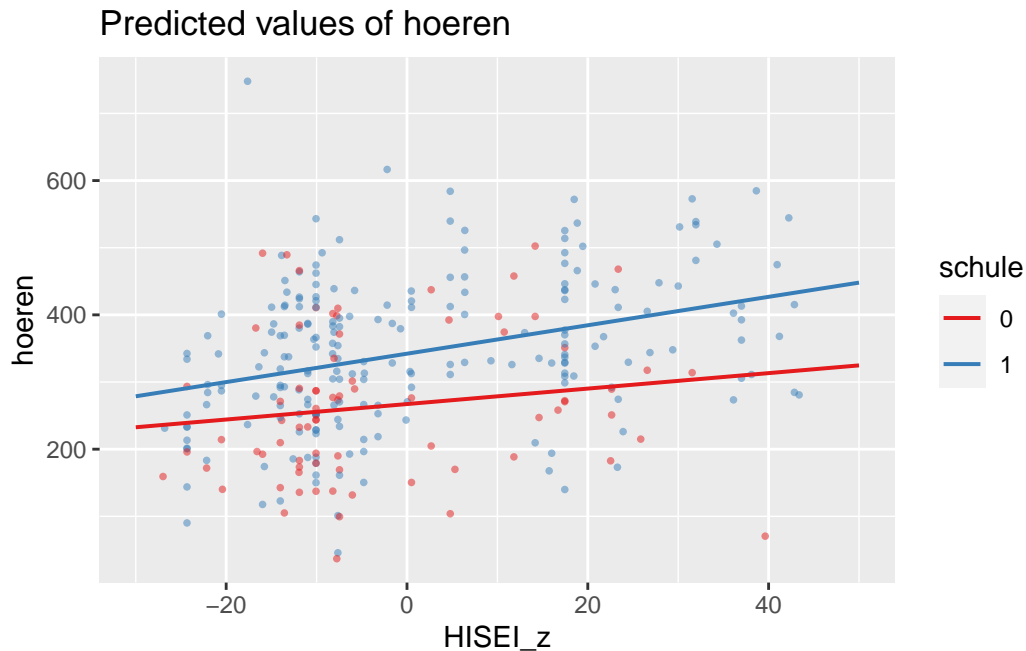
Effekt ist Abstand zwischen den Geraden ($\widehat{ATE} = \alpha_2 = 72.99$)

Aufgabe 5: Generalisierte ANCOVA

```
m3 <- lm(hoeren ~ HISEI_z * schule, spf2)
summary(m3)$coef
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	267.1818702	12.3917244	21.561315	8.039943e-62
HISEI_z	1.1514127	0.8334636	1.381479	1.682137e-01
schule1	75.0287695	14.4028985	5.209283	3.640344e-07
HISEI_z:schule1	0.9649005	0.9274274	1.040405	2.990334e-01

```
plot_model(m3, type = "pred",
  terms = c("HISEI_z", "schule"),
  show.data = TRUE, dot.size = 1, # graph. Parameter
  ci.lvl = NA)
```



ATE und ATT berechnen

Für die Berechnung des ATT brauchen wir den Mittelwert der Kovariaten in der Treatmentgruppe ($E(Z | X = 1)$). Für den ATE benutzen wir dass $E(Z) = 0$, da wir unsere Kovariate am Gesamtmittelwert zentriert haben.

```
# Mittelwert der zentrierten Kovariaten in Treatmentgruppe
mean(sp2$HISEI_z[sp2$schule==1])
```

```
[1] 1.038332
```

$$\begin{aligned}\widehat{ATE} &= \alpha_2 = 75.03 \\ \widehat{ATT}_{X=1} &= \alpha_2 + \alpha_3 \cdot E(Z|X=1) \\ &= 75.0287695 + 0.9649005 \cdot 1.038332 = 76.03\end{aligned}$$

Aufgabe 6: Bedingter Effekt

Effekt bei minimalem sozioökonomischem Status:

```
# Minimaler soz. Status
min(spf2$HISEI_z)
```

```
[1] -26.98398
```

$$\begin{aligned}
 E[g_1(Z = -26.98)] &= \alpha_2 + \alpha_3 \cdot \min(Z) \\
 &= 75.0287695 + 0.9649005 \cdot -26.98398 = 48.99
 \end{aligned}$$

Aufgabe 7: EffectLiteR

```
library(EffectLiteR)           # Paket laden
# Modell ohne Kovariate
effectLite(y = " hoeren", x = "schule", control = "0", data = spf2)
```

```
----- Message -----
```

```
-- model converged succesfully --
```

```
----- Variables -----
```

```
Outcome variable Y: hoeren
```

```
Treatment variable X: schule (Reference group: 0)
```

```
Levels of Treatment Variable X
```

X	schule (original)	Indicator
0	0	I_X=0
1	1	I_X=1

```
----- Regression Model -----
```

```
E(Y|X) = g0() + g1()*I_X=1
g0() = g000
g1() = g100
```

Intercept Function g0() [Reference group: 0]

Coefficient	Estimate	SE	Est./SE	p-value
g000	263.89	12.422	21.243	0

Effect Function g1() [schule: 1 vs. 0]

Coefficient	Estimate	SE	Est./SE	p-value
g100	80.518	14.612	5.511	0

----- Cell Counts -----

Cell Counts

This table shows cell counts including missings.
See also output under lavaan results for number of observations actually used in the analysis.

schule	0	1
	77	212

----- Main Hypotheses -----

H0: No average effects: $E[g1()] = 0$

	Wald Chi-Square	df	p-value
No average effects	30.4	1	3.58e-08

----- Adjusted Means -----

	Estimate	SE	Est./SE
Adj.Mean0	264	12.42	21.2
Adj.Mean1	344	7.69	44.8

----- Average Effects -----

	Estimate	SE	Est./SE	p-value	Effect Size
E[g1()]	80.5	14.6	5.51	3.58e-08	0.739

```
# trad. ANCOVA
effectLite(y = " hoeren", x = "schule", control = "0", data = spf2,
           z = "HISEI_z", interactions = "none")
```

----- Message -----

-- model converged succesfully --

----- Variables -----

Outcome variable Y: hoeren
 Treatment variable X: schule (Reference group: 0)
 Continuous covariates in Z=(Z1): Z1=HISEI_z

Levels of Treatment Variable X

X	schule (original)	Indicator
0	0	I_X=0
1	1	I_X=1

----- Regression Model -----

$$E(Y|X,Z) = g_0(Z) + g_1(Z) \cdot I_X=1$$

$$g_0(Z) = g_{000} + g_{001} \cdot Z_1$$

$$g_1(Z) = g_{100} + g_{101} \cdot Z_1$$

Intercept Function g0(Z) [Reference group: 0]

Coefficient	Estimate	SE	Est./SE	p-value
g000	269.433	12.387	21.751	0
g001	1.939	0.363	5.343	0

Effect Function g1(Z) [schule: 1 vs. 0]

Coefficient	Estimate	SE	Est./SE	p-value
-------------	----------	----	---------	---------

g100	72.962	14.378	5.074	0
g101	0.000	NA	NA	NA

----- Cell Counts -----

Cell Counts

This table shows cell counts including missings.
See also output under lavaan results for number of observations actually used in the analysis.

```
schule    0    1
          77 212
```

----- Main Hypotheses -----

H0: No average effects: $E[g_1(Z)] = 0$
H0: No covariate effects in control group: $g_0(Z) = \text{constant}$
H0: No treatment*covariate interaction: $g_1(Z) = \text{constant}$
H0: No treatment effects: $g_1(Z) = 0$

	Wald Chi-Square	df	p-value
No average effects	25.7	1	3.89e-07
No covariate effects in control group	28.5	1	9.15e-08
No treatment*covariate interaction	NA	0	NA
No treatment effects	25.7	1	3.89e-07

----- Adjusted Means -----

	Estimate	SE	Est./SE
Adj.Mean0	269	12.54	21.5
Adj.Mean1	342	7.51	45.6

----- Average Effects -----

	Estimate	SE	Est./SE	p-value	Effect Size
$E[g_1(Z)]$	73	14.4	5.07	3.89e-07	0.652

----- Effects given a Treatment Condition -----

	Estimate	SE	Est./SE	p-value	Effect Size
E[g1(Z) X=0]	73	14.4	5.07	3.89e-07	0.652
E[g1(Z) X=1]	73	14.4	5.07	3.89e-07	0.652

```
# gen. ANCOVA
effectLite(y = " hoeren", x = "schule", control = "0", data = spf2,
           z = "HISEI_z")
```

----- Message -----

-- model converged succesfully --

----- Variables -----

Outcome variable Y: hoeren
 Treatment variable X: schule (Reference group: 0)
 Continuous covariates in Z=(Z1): Z1=HISEI_z

Levels of Treatment Variable X

X	schule (original)	Indicator
0	0	I_X=0
1	1	I_X=1

----- Regression Model -----

$$E(Y|X,Z) = g_0(Z) + g_1(Z) \cdot I_X=1$$

$$g_0(Z) = g_{000} + g_{001} \cdot Z_1$$

$$g_1(Z) = g_{100} + g_{101} \cdot Z_1$$

Intercept Function $g_0(Z)$ [Reference group: 0]

Coefficient	Estimate	SE	Est./SE	p-value
g000	267.182	12.507	21.362	0.000

g001 1.151 0.841 1.369 0.171

Effect Function g1(Z) [schule: 1 vs. 0]

Coefficient	Estimate	SE	Est./SE	p-value
g100	75.029	14.455	5.191	0.000
g101	0.965	0.932	1.035	0.301

----- Cell Counts -----

Cell Counts

This table shows cell counts including missings.
See also output under lavaan results for number of observations
actually used in the analysis.

schule 0 1

77 212

----- Main Hypotheses -----

H0: No average effects: $E[g1(Z)] = 0$
H0: No covariate effects in control group: $g0(Z) = \text{constant}$
H0: No treatment*covariate interaction: $g1(Z) = \text{constant}$
H0: No treatment effects: $g1(Z) = 0$

	Wald Chi-Square	df	p-value
No average effects	26.82	1	2.23e-07
No covariate effects in control group	1.87	1	1.71e-01
No treatment*covariate interaction	1.07	1	3.01e-01
No treatment effects	27.05	2	1.34e-06

----- Adjusted Means -----

	Estimate	SE	Est./SE
Adj.Mean0	267	12.56	21.3
Adj.Mean1	342	7.56	45.3

----- Average Effects -----					
	Estimate	SE	Est./SE	p-value	Effect Size
E[g1(Z)]	75	14.5	5.18	2.23e-07	0.688

----- Effects given a Treatment Condition -----					
	Estimate	SE	Est./SE	p-value	Effect Size
E[g1(Z) X=0]	72.3	14.4	5.01	5.41e-07	0.663
E[g1(Z) X=1]	76.0	14.7	5.18	2.18e-07	0.698