ANOVA 2 (Fortsetzung)

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Wiederholung

Types of sum of squares

Factorial ANOVA with repeated measures

Beispiel (Koma-Saufen)

Zweifache ANOVA mit wiederholten Messungen vergleicht verschiedene Gruppen im Falle von zwei unabhängigen Variablen, wobei alle Teilnehmer an allen Versuchsbedingungen teilgenommen haben.

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Hat die Werbung mit negativen visuellen Inhalten eine Auswirkung auf die Einstellung zum excessiven Alkoholkomsum?

Daten (Koma-Saufen)

Table 1: Datensatz über Einstellung zum Trinken und Werbung [A. Field]

beerpos	beerneg	beerneut	winepos	wineneg	wineneut	waterpos	waterneg	waterneu	participant
1	6	5	38	-5	4	10	-14	-2	P1
43	30	8	20	-12	4	9	-10	-13	P2
15	15	12	20	-15	6	6	-16	1	P3
40	30	19	28	-4	0	20	-10	2	P4
8	12	8	11	-2	6	27	5	-5	P5
17	17	15	17	-6	6	9	-6	-13	P6
30	21	21	15	-2	16	19	-20	3	P7
34	23	28	27	-7	7	12	-12	2	P8
34	20	26	24	-10	12	12	-9	4	P9
26	27	27	23	-15	14	21	-6	0	P10

Beispiel

```
##     participant   groups attitude drink  imagery
## 1            P1  beerpos        1  Beer  Postive
## 21           P1  beerneg        6  Beer Negative
## 41           P1 beerneut        5  Beer  Neutral
## 61           P1  winepos       38  Wine  Postive
## 81           P1  wineneg       -5  Wine Negative
## 101          P1 wineneut        4  Wine  Neutral
## 121          P1 waterpos       10 Water  Postive
## 141          P1 waterneg      -14 Water Negative
## 161          P1 waterneu       -2 Water  Neutral
## 10          P10  beerpos       26  Beer  Postive
## 30          P10  beerneg       27  Beer Negative
## 50          P10 beerneut       27  Beer  Neutral
## 70          P10  winepos       23  Wine  Postive
## 90          P10  wineneg      -15  Wine Negative
## 110         P10 wineneut       14  Wine  Neutral
## 130         P10 waterpos       21 Water  Postive
## 150         P10 waterneg       -6 Water Negative
## 170         P10 waterneu        0 Water  Neutral
## 11          P11  beerpos        1  Beer  Postive
## 31          P11  beerneg      -19  Beer Negative
## 51          P11 beerneut      -10  Beer  Neutral
## 71          P11  winepos       28  Wine  Postive
## 91          P11  wineneg      -13  Wine Negative
## 111         P11 wineneut       13  Wine  Neutral
## 131         P11 waterpos       33 Water  Postive
## 151         P11 waterneg       -2 Water Negative
## 171         P11 waterneu        9 Water  Neutral
## 12          P12  beerpos        7  Beer  Postive
## 32          P12  beerneg      -18  Beer Negative
## 52          P12 beerneut        6  Beer  Neutral
## 72          P12  winepos       26  Wine  Postive
## 92          P12  wineneg      -16  Wine Negative
## 112         P12 wineneut       19  Wine  Neutral
## 132         P12 waterpos       23 Water  Postive
## 152         P12 waterneg      -17 Water Negative
## 172         P12 waterneu        5 Water  Neutral
## 13          P13  beerpos       22  Beer  Postive
## 33          P13  beerneg       -8  Beer Negative
## 53          P13 beerneut        4  Beer  Neutral
```

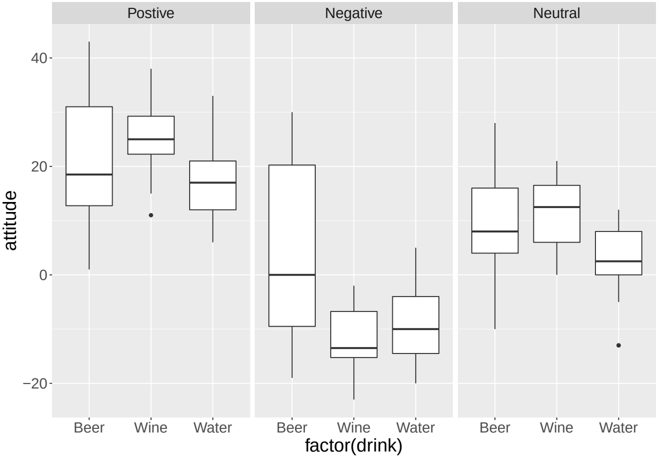

Figure 1: Boxplots von Daten über Alkoholkomsumeinstellung.

Beispiel (Deskriptive Statistik) I

```
## : Beer
## : Postive
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##   18.5000000   21.0500000    2.9086758    6.0879284  169.2078947   13.0079935
##     coef.var
##    0.6179569
## ------------------------------------------------------------
## : Wine
## : Postive
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##   25.0000000   25.3500000    1.5066083    3.1533673   45.3973684    6.7377569
##     coef.var
##    0.2657892
## ------------------------------------------------------------
## : Water
## : Postive
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##   17.0000000   17.4000000    1.5818044    3.3107547   50.0421053    7.0740445
##     coef.var
##    0.4065543
## ------------------------------------------------------------
## : Beer
## : Negative
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##     0.000000     4.450000     3.869227     8.098386   299.418421    17.303711
##     coef.var
##     3.888474
## ------------------------------------------------------------
## : Wine
## : Negative
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##  -13.5000000  -12.0000000    1.3822179    2.8930153   38.2105263    6.1814664
##     coef.var
##   -0.5151222
## ------------------------------------------------------------
## : Water
```

Beispiel (Deskriptive Statistik) II

```
## : Negative
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##  -10.0000000   -9.2000000    1.5210799    3.1836569   46.2736842    6.8024763
##     coef.var
##   -0.7393996
## ------------------------------------------------------------
## : Beer
## : Neutral
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##     8.000000    10.000000     2.302173     4.818503   106.000000    10.295630
##     coef.var
##     1.029563
## ------------------------------------------------------------
## : Wine
## : Neutral
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##   12.5000000   11.6500000    1.3959999    2.9218614   38.9763158    6.2431015
##     coef.var
##    0.5358885
## ------------------------------------------------------------
## : Water
## : Neutral
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##     2.500000     2.350000     1.529147     3.200541    46.765789     6.838552
##     coef.var
##     2.910022
```

Kontraste für Getränke

1. Ist die Wirkung für *alkoholische* und *nicht alkoholische* Getränke unterschiedlich?

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2. Ist die Wirkung für *verschiedene alkoholische* Getränke unterschiedlich?

Kontraste für Getränke

1. Ist die Wirkung für *alkoholische* und *nicht alkoholische* Getränke unterschiedlich?
2. Ist die Wirkung für *verschiedene alkoholische* Getränke unterschiedlich?

```
##       AlcoholvsWater BeervsWine
## Beer               1         -1
## Wine               1          1
## Water             -2          0
```

Kontraste für Bilder

1. Haben *negative* Bilder andere Wirkung im Vergleich zu den anderen Formen?

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1. Haben *negative* Bilder andere Wirkung im Vergleich zu den anderen Formen?
2. Ist die Wirkung unterschiedlich für *positive* und *negative* Bilder?

```
##          NegativevsOther PositivevsNeutral
## Postive                1                -1
## Negative              -2                 0
## Neutral                1                 1
```

Factorielle ANOVA mit wiederholten Messungen

```
library(ez)
attitudeModel <- ezANOVA(data = longAttitude, dv = .(attitude), wid = .(participant),
    within = .(imagery, drink), type = 3, detailed = TRUE)
```

```
## Warning: Converting "participant" to factor for ANOVA.
```

```
attitudeModel
```

```
## $ANOVA
##          Effect DFn DFd       SSn      SSd          F            p p<.05
## 1   (Intercept)   1  19 11218.006 1920.106 111.005411 2.255322e-09     *
## 2       imagery   2  38 21628.678 3352.878 122.564825 2.680197e-17     *
## 3         drink   2  38  2092.344 7785.878   5.105981 1.086293e-02     *
## 4 imagery:drink   4  76  2624.422 2906.689  17.154922 4.589040e-10     *
##         ges
## 1 0.4126762
## 2 0.5753191
## 3 0.1158687
## 4 0.1411741
##
## $`Mauchly's Test for Sphericity`
##          Effect         W            p p<.05
## 2       imagery 0.6621013 2.445230e-02     *
## 3         drink 0.2672411 6.952302e-06     *
## 4 imagery:drink 0.5950440 4.356587e-01
##
## $`Sphericity Corrections`
##          Effect       GGe        p[GG] p[GG]<.05       HFe        p[HF]
## 2       imagery 0.7474407 1.757286e-13         * 0.7968420 3.142804e-14
## 3         drink 0.5771143 2.976868e-02         * 0.5907442 2.881391e-02
## 4 imagery:drink 0.7983979 1.900249e-08         * 0.9785878 6.809640e-10
##   p[HF]<.05
## 2         *
## 3         *
## 4         *
```

- Signifikanz vom Mauchly's Test für **drink** und **imagery** deutet auf Nichterfüllung der Spherizität. Daher wird *F*-Verhältnis angepasst.

Hauptwirkung (main effect) von Getränk

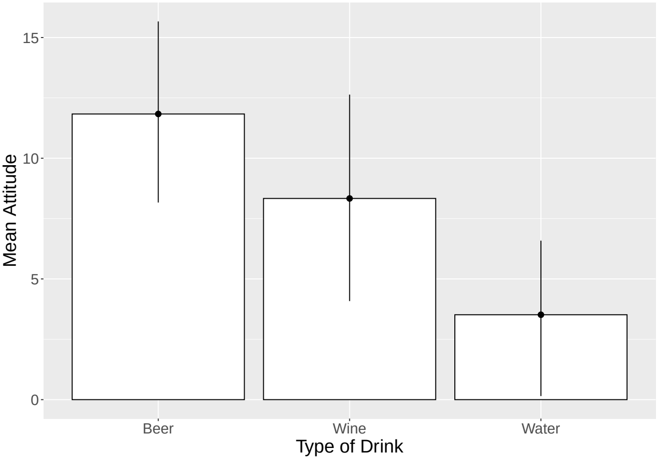

Figure 2: Balkendiagramme für die Hauptwirkung von Getränk.

Getränk: deskriptive Statistik

```
by(longAttitude$attitude, longAttitude$drink, stat.desc, basic = FALSE)
```

```
## longAttitude$drink: Beer
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##    12.500000    11.833333     1.972576     3.947115   233.463277    15.279505
##     coef.var
##     1.291226
## ------------------------------------------------------------
## longAttitude$drink: Wine
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##    12.000000     8.333333     2.166080     4.334316   281.514124    16.778383
##     coef.var
##     2.013406
## ------------------------------------------------------------
## longAttitude$drink: Water
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##     3.500000     3.516667     1.666806     3.335272   166.694633    12.911028
##     coef.var
##     3.671382
```

Hauptwirkung (main effect) von Bild

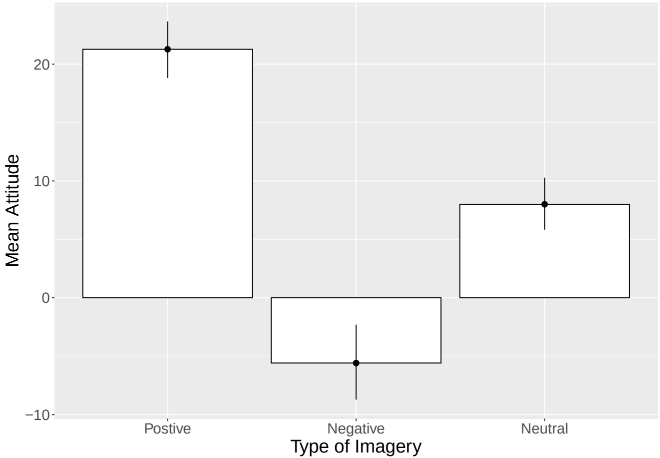

Figure 3: Balkendiagramme für die Hauptwirkung von Bild.

Bild: deskriptive Statistik

```
by(longAttitude$attitude, longAttitude$imagery, stat.desc, basic = FALSE)
```

```
## longAttitude$imagery: Postive
##       median        mean     SE.mean CI.mean.0.95         var     std.dev
##   20.5000000  21.2666667   1.2646579    2.5305747  95.9615819   9.7959983
##     coef.var
##    0.4606269
## ------------------------------------------------------------
## longAttitude$imagery: Negative
##       median        mean     SE.mean CI.mean.0.95         var     std.dev
##    -9.000000   -5.583333    1.713405     3.428516  176.145480   13.271981
##     coef.var
##    -2.377071
## ------------------------------------------------------------
## longAttitude$imagery: Neutral
##       median        mean     SE.mean CI.mean.0.95         var     std.dev
##     7.000000    8.000000    1.143392     2.287922   78.440678    8.856674
##     coef.var
##     1.107084
```

Wechselwirkungen **drink** × **imagery** (interactions)

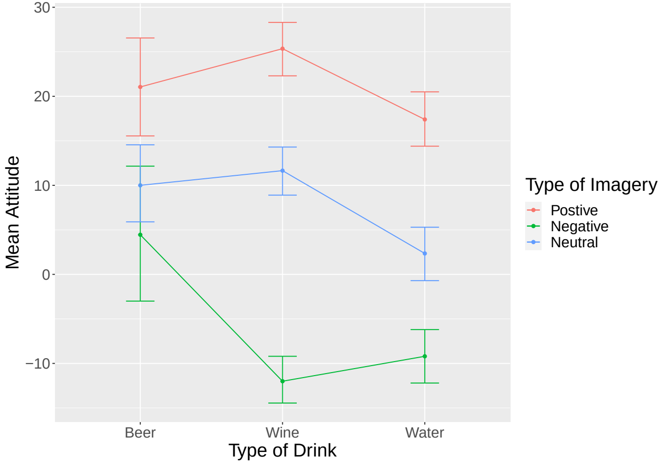

Figure 4: Wechselwirkung zwischen drink und imagery. Man sieht, dass die negativen Bilder andere Wirkung haben als positive oder neutrale Bilder.

Paarweiser t-Test (post hoc Test)

```r
pairwise.t.test(longAttitude$attitude, longAttitude$groups, paired = TRUE, p.adjust.method = "bonferroni")
```

```
##
##  Pairwise comparisons using paired t tests
##
## data:  longAttitude$attitude and longAttitude$groups
##
##          beerpos beerneg beerneut winepos wineneg wineneut waterpos waterneg
## beerneg  0.00217 -       -        -       -       -        -        -
## beerneut 0.01982 1.00000 -        -       -       -        -        -
## winepos  1.00000 0.01105 0.00310  -       -       -        -        -
## wineneg  5.6e-08 0.00265 2.0e-07  1.9e-10 -       -        -        -
## wineneut 0.39905 1.00000 1.00000  2.2e-05 2.3e-07 -        -        -
## waterpos 1.00000 0.47584 1.00000  0.07300 1.3e-09 0.10547  -        -
## waterneg 2.9e-06 0.18860 0.00010  3.2e-10 1.00000 1.1e-07  4.9e-11  -
## waterneu 0.00212 1.00000 0.74838  4.3e-10 0.00041 8.1e-05  9.0e-07  0.00068
##
## P value adjustment method: bonferroni
```

```r
options(digits = 7)
```

Faktorelles Design mit wiederholten Messungen als GLM

```
library(nlme)
baseline <- lme(attitude ~ 1, random = ~1 | participant/drink/imagery, data = longAttitude,
    method = "ML")
```

random = ~1|participant/drink/imagery bedeutet, dass für den zufälligen Teil des Modells die Variablen **drink** und **imagery** s.g. *nested* Variablen innerhalb der Variablen **participant** sind. Die Werte für diese Variablen sind für jeden Teilnehmer vorhanden.

Faktorelles Design mit wiederholten Messungen als GLM

```r
library(nlme)
baseline <- lme(attitude ~ 1, random = ~1 | participant/drink/imagery, data = longAttitude,
    method = "ML")
```

random $=$ *~1|participant/drink/imagery* bedeutet, dass für den zufälligen Teil des Modells die Variablen **drink** und **imagery** s.g. *nested* Variablen innerhalb der Variablen **participant** sind. Die Werte für diese Variablen sind für jeden Teilnehmer vorhanden.

Falls wir den Haupteffekt von einzelnen Faktoren untersuchen wollen, müssen wir sie dem Modell beifügen.

```r
drinkModel <- update(baseline, . ~ . + drink)
imageryModel <- update(drinkModel, . ~ . + imagery)
attitudeModel <- update(imageryModel, . ~ . + drink:imagery)
```

ANOVA-Vergleich von Modellen

```
anova(baseline, drinkModel, imageryModel, attitudeModel)
```

```
##               Model df      AIC      BIC    logLik   Test   L.Ratio p-value
## baseline          1  5 1503.590 1519.555 -746.7950
## drinkModel        2  7 1498.461 1520.812 -742.2306 1 vs 2   9.12891  0.0104
## imageryModel      3  9 1350.529 1379.265 -666.2644 2 vs 3 151.93237  <.0001
## attitudeModel     4 13 1316.512 1358.020 -645.2560 3 vs 4  42.01676  <.0001
```

Modell-Ausgabe I

```
summary(attitudeModel)
```

```
## Linear mixed-effects model fit by maximum likelihood
##  Data: longAttitude
##        AIC     BIC   logLik
##   1316.512 1358.02 -645.256
##
## Random effects:
##  Formula: ~1 | participant
##          (Intercept)
## StdDev: 0.0007437312
##
##  Formula: ~1 | drink %in% participant
##         (Intercept)
## StdDev:    6.044143
##
##  Formula: ~1 | imagery %in% drink %in% participant
##         (Intercept)  Residual
## StdDev:    7.217035 0.2803831
##
## Fixed effects: attitude ~ drink + imagery + drink:imagery
##                                                Value Std.Error  DF   t-value
## (Intercept)                                 7.894444 0.9726049 114  8.116805
## drinkAlcoholvsWater                         2.188889 0.6877355  38  3.182748
## drinkBeervsWine                            -1.750000 1.1911928  38 -1.469116
## imageryNegativevsOther                      6.738889 0.3905470 114 17.255002
## imageryPositivevsNeutral                   -6.633333 0.6764472 114 -9.806136
## drinkAlcoholvsWater:imageryNegativevsOther    0.190278 0.2761584 114  0.689017
## drinkBeervsWine:imageryNegativevsOther       3.237500 0.4783204 114  6.768475
## drinkAlcoholvsWater:imageryPositivevsNeutral  0.445833 0.4783204 114  0.932081
## drinkBeervsWine:imageryPositivevsNeutral    -0.662500 0.8284753 114 -0.799662
##                                            p-value
## (Intercept)                                 0.0000
## drinkAlcoholvsWater                         0.0029
## drinkBeervsWine                             0.1500
## imageryNegativevsOther                      0.0000
```

Modell-Ausgabe II

```
## imageryPositivevsNeutral                     0.0000
## drinkAlcoholvsWater:imageryNegativevsOther    0.4922
## drinkBeervsWine:imageryNegativevsOther        0.0000
## drinkAlcoholvsWater:imageryPositivevsNeutral  0.3533
## drinkBeervsWine:imageryPositivevsNeutral      0.4256
##  Correlation:
##                                              (Intr) drnkAW drnkBW imgrNO imgrPN
## drinkAlcoholvsWater                          0
## drinkBeervsWine                              0      0
## imageryNegativevsOther                       0      0      0
## imageryPositivevsNeutral                     0      0      0      0
## drinkAlcoholvsWater:imageryNegativevsOther   0      0      0      0      0
## drinkBeervsWine:imageryNegativevsOther       0      0      0      0      0
## drinkAlcoholvsWater:imageryPositivevsNeutral 0      0      0      0      0
## drinkBeervsWine:imageryPositivevsNeutral     0      0      0      0      0
##                                              dAW:NO dBW:NO dAW:PN
## drinkAlcoholvsWater
## drinkBeervsWine
## imageryNegativevsOther
## imageryPositivevsNeutral
## drinkAlcoholvsWater:imageryNegativevsOther
## drinkBeervsWine:imageryNegativevsOther       0
## drinkAlcoholvsWater:imageryPositivevsNeutral 0      0
## drinkBeervsWine:imageryPositivevsNeutral     0      0      0
##
## Standardized Within-Group Residuals:
##          Min           Q1          Med           Q3          Max
## -0.086767486 -0.020849266  0.000768403  0.025120590  0.103677229
##
## Number of Observations: 180
## Number of Groups:
##                        participant               drink %in% participant
##                                 20                                   60
## imagery %in% drink %in% participant
##                                180
```

Post hoc-Tests (**drink**) I

```r
library(multcomp)
postHocs <- glht(attitudeModel, linfct = mcp(drink = "Tukey"))
```

```
## Warning in mcp2matrix(model, linfct = linfct): covariate interactions found --
## default contrast might be inappropriate
```

```r
summary(postHocs)
```

```
##
##   Simultaneous Tests for General Linear Hypotheses
##
## Multiple Comparisons of Means: Tukey Contrasts
##
##
## Fit: lme.formula(fixed = attitude ~ drink + imagery + drink:imagery,
##     data = longAttitude, random = ~1 | participant/drink/imagery,
##     method = "ML")
##
## Linear Hypotheses:
##                   Estimate Std. Error z value Pr(>|z|)
## Wine - Beer == 0    -3.500      2.322  -1.507  0.28743
## Water - Beer == 0   -8.317      2.322  -3.582  0.00102 **
## Water - Wine == 0   -4.817      2.322  -2.074  0.09522 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
```

```r
confint(postHocs)
```

Post hoc-Tests (**drink**) II

```
##
##   Simultaneous Confidence Intervals
##
## Multiple Comparisons of Means: Tukey Contrasts
##
##
## Fit: lme.formula(fixed = attitude ~ drink + imagery + drink:imagery,
##     data = longAttitude, random = ~1 | participant/drink/imagery,
##     method = "ML")
##
## Quantile = 2.3432
## 95% family-wise confidence level
##
##
## Linear Hypotheses:
##                    Estimate lwr      upr
## Wine - Beer == 0   -3.5000  -8.9411   1.9411
## Water - Beer == 0  -8.3167 -13.7577  -2.8756
## Water - Wine == 0  -4.8167 -10.2577   0.6244
```

Post hoc-Tests (**drink**) I

```r
postHocs <- glht(attitudeModel, linfct = mcp(imagery = "Tukey"))
```

```
## Warning in mcp2matrix(model, linfct = linfct): covariate interactions found --
## default contrast might be inappropriate
```

```r
summary(postHocs)
```

```
##
##   Simultaneous Tests for General Linear Hypotheses
##
## Multiple Comparisons of Means: Tukey Contrasts
##
##
## Fit: lme.formula(fixed = attitude ~ drink + imagery + drink:imagery,
##     data = longAttitude, random = ~1 | participant/drink/imagery,
##     method = "ML")
##
## Linear Hypotheses:
##                          Estimate Std. Error z value Pr(>|z|)
## Negative - Postive == 0  -26.850      1.319  -20.36   <2e-16 ***
## Neutral - Postive == 0   -13.267      1.319  -10.06   <2e-16 ***
## Neutral - Negative == 0   13.583      1.319   10.30   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Adjusted p values reported -- single-step method)
```

```r
confint(postHocs)
```

Post hoc-Tests (**drink**) II

```
##
##   Simultaneous Confidence Intervals
##
## Multiple Comparisons of Means: Tukey Contrasts
##
##
## Fit: lme.formula(fixed = attitude ~ drink + imagery + drink:imagery,
##     data = longAttitude, random = ~1 | participant/drink/imagery,
##     method = "ML")
##
## Quantile = 2.3437
## 95% family-wise confidence level
##
##
## Linear Hypotheses:
##                         Estimate lwr      upr
## Negative - Postive == 0 -26.8500 -29.9405 -23.7595
## Neutral - Postive == 0  -13.2667 -16.3572 -10.1761
## Neutral - Negative == 0  13.5833  10.4928  16.6739
```

mixed design ANOVA

Mixed design ANOVA

Mischung aus zwischen-Gruppen-Variablen und Variablen mit wiederholten Messungen nennt man *gemischtes Design*.

Mixed design ANOVA

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Es is empfehlenswert mit nicht mehr als *drei* unabhängigen Variablen zu arbeiten. Anderenfalls können die Interaktionen schwer interpretiert werden.

Beispiel (Speed Dating)

Beispiel: Beim Speed Dating werden die Personen beurteilt nach *Attraktivität* (**looks**) und *Charisma* (**personality**). Die beiden Variablen beinhalten wiederholte Messungen. Die Person, die die Beurteilung abgibt, kann mänlich oder weiblich sein. Deher ist Geschlecht (**gender**) eine zwischen-Gruppen-Variable.

Beispiel (Speed Dating) (1)

Table 2: Datensatz über Speed Dating [A. Field]

participant	gender	att_high	av_high	ug_high	att_some	av_some	ug_some	att_none	av_none	ug_non
P01	Male	86	84	67	88	69	50	97	48	4
P02	Male	91	83	53	83	74	48	86	50	4
P03	Male	89	88	48	99	70	48	90	45	4
P04	Male	89	69	58	86	77	40	87	47	5
P05	Male	80	81	57	88	71	50	82	50	4
P06	Male	80	84	51	96	63	42	92	48	4
P07	Male	89	85	61	87	79	44	86	50	4
P08	Male	100	94	56	86	71	54	84	54	4
P09	Male	90	74	54	92	71	58	78	38	4
P10	Male	89	86	63	80	73	49	91	48	3

Beispiel (Speed Dating) (2)

```
##     participant gender   groups dateRating personality       looks
## 1           P01   Male att_high         86 Charismatic Attractive
## 21          P01   Male  av_high         84 Charismatic    Average
## 41          P01   Male  ug_high         67 Charismatic       Ugly
## 61          P01   Male att_some         88     Average Attractive
## 81          P01   Male  av_some         69     Average    Average
## 101         P01   Male  ug_some         50     Average       Ugly
## 121         P01   Male att_none         97     Dullard Attractive
## 141         P01   Male  av_none         48     Dullard    Average
## 161         P01   Male  ug_none         47     Dullard       Ugly
## 2           P02   Male att_high         91 Charismatic Attractive
```

Speed Dating (Boxplots)

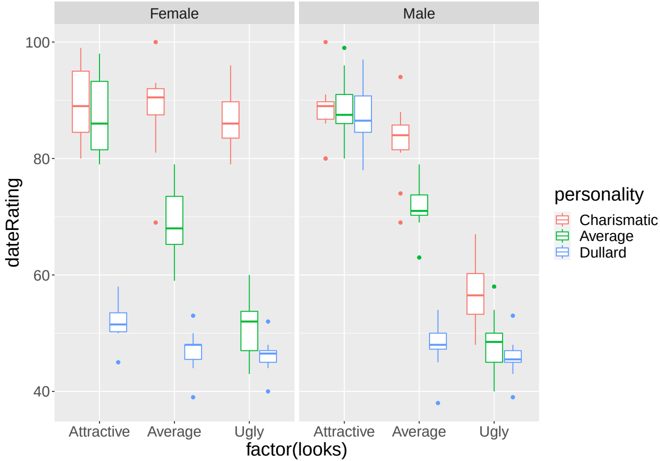

Figure 5: Boxplots von Daten über Speed Dating.

Speed Dating (Deskriptive Statistik) I

```
by(speedData$dateRating, list(speedData$looks, speedData$personality, speedData$gender),
    stat.desc, basic = FALSE)
```

```
## : Attractive
## : Charismatic
## : Female
##       median        mean      SE.mean CI.mean.0.95          var      std.dev
##  89.00000000 89.60000000   2.09867683   4.74753683  44.04444444   6.63659886
##      coef.var
##   0.07406918
## ------------------------------------------------------------
## : Average
## : Charismatic
## : Female
##       median        mean      SE.mean CI.mean.0.95          var      std.dev
##  90.50000000 88.40000000   2.63396617   5.95844544  69.37777778   8.32933237
##      coef.var
##   0.09422322
## ------------------------------------------------------------
## : Ugly
## : Charismatic
## : Female
##       median        mean      SE.mean CI.mean.0.95          var      std.dev
##  86.00000000 86.70000000   1.71949605   3.88977031  29.56666667   5.43752395
##      coef.var
##   0.06271654
## ------------------------------------------------------------
## : Attractive
## : Average
## : Female
##       median        mean      SE.mean CI.mean.0.95          var      std.dev
##  86.00000000 87.10000000   2.15225979   4.86874991  46.32222222   6.80604307
##      coef.var
##   0.07814056
## ------------------------------------------------------------
## : Average
```

Speed Dating (Deskriptive Statistik) II

```
## : Average
## : Female
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##  68.00000000  68.90000000   1.88237439   4.25822670  35.43333333   5.95259047
##     coef.var
##   0.08639464
## ------------------------------------------------------------------
## : Ugly
## : Average
## : Female
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##   52.0000000   51.2000000    1.7243356    3.9007182   29.7333333    5.4528280
##     coef.var
##    0.1065005
## ------------------------------------------------------------------
## : Attractive
## : Dullard
## : Female
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##  51.50000000  51.80000000   1.09341463   2.47347574  11.95555556   3.45768066
##     coef.var
##   0.06675059
## ------------------------------------------------------------------
## : Average
## : Dullard
## : Female
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##  48.00000000  47.00000000   1.18321596   2.67662045  14.00000000   3.74165739
##     coef.var
##   0.07960973
## ------------------------------------------------------------------
## : Ugly
## : Dullard
## : Female
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##  46.50000000  46.10000000   0.97125349   2.19712803   9.43333333   3.07137320
```

Speed Dating (Deskriptive Statistik) III

```
##     coef.var
##   0.06662415
## ------------------------------------------------------------
## : Attractive
## : Charismatic
## : Male
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##  89.00000000 88.30000000   1.80154255   4.07537238  32.45555556   5.69697776
##     coef.var
##   0.06451843
## ------------------------------------------------------------
## : Average
## : Charismatic
## : Male
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##  84.00000000 82.80000000   2.21509970   5.01090365  49.06666667   7.00476029
##     coef.var
##   0.08459855
## ------------------------------------------------------------
## : Ugly
## : Charismatic
## : Male
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##    56.500000    56.800000     1.812304     4.099716    32.844444     5.731007
##     coef.var
##     0.100898
## ------------------------------------------------------------
## : Attractive
## : Average
## : Male
##       median         mean      SE.mean CI.mean.0.95          var      std.dev
##  87.50000000 88.50000000   1.81506045   4.10595200  32.94444444   5.73972512
##     coef.var
##   0.06485565
## ------------------------------------------------------------
## : Average
```

Speed Dating (Deskriptive Statistik) IV

```
## : Average
## : Male
##      median         mean      SE.mean CI.mean.0.95          var      std.dev
##  71.00000000  71.80000000   1.39682179   3.15983042  19.51111111   4.41713834
##     coef.var
##   0.06152003
## ------------------------------------------------------------
## : Ugly
## : Average
## : Male
##      median         mean      SE.mean CI.mean.0.95          var      std.dev
##   48.5000000   48.3000000    1.7000000    3.8456672   28.9000000    5.3758720
##     coef.var
##    0.1113017
## ------------------------------------------------------------
## : Attractive
## : Dullard
## : Male
##      median         mean      SE.mean CI.mean.0.95          var      std.dev
##   86.5000000   87.3000000    1.7194961    3.8897703   29.5666667    5.4375239
##     coef.var
##    0.0622855
## ------------------------------------------------------------
## : Average
## : Dullard
## : Male
##      median         mean      SE.mean CI.mean.0.95          var      std.dev
##  48.00000000  47.80000000   1.32329555   2.99350251  17.51111111   4.18462795
##     coef.var
##   0.08754452
## ------------------------------------------------------------
## : Ugly
## : Dullard
## : Male
##      median         mean      SE.mean CI.mean.0.95          var      std.dev
##  45.50000000  45.80000000   1.13333333   2.56377812  12.84444444   3.58391468
```

Speed Dating (Deskriptive Statistik) V

```
##     coef.var
##   0.07825141
```

Kontraste

Man betrachte die untersten Kategorien (*Dullard* und *Ugly*) als Kontrolle.

1. Kontrast für **personality** vergleicht *Average* und *Charismatic* mit *Dullard*.
2. Kontrast für **personality** vergleicht *Charismatic* mit *Average*.
3. Kontrast für **looks** vergleicht *Average* und *Attractive* mit *Ugly*.
4. Kontrast für **looks** vergleicht *Attractive* mit *Average*.

(orthogonale) Kontraste

(orthogonale) Kontraste

```
##             SomevsNone HivsAv
## Charismatic          1      1
## Average              1     -1
## Dullard             -2      0
```

(orthogonale) Kontraste

```
##             SomevsNone HivsAv
## Charismatic          1      1
## Average              1     -1
## Dullard             -2      0
```

```
##            AttractivevsUgly AttractivevsAv
## Attractive                1              1
## Average                   1             -1
## Ugly                     -2              0
```

Factorielle ANOVA mit gemischtem Design I

between bedeutet dass **gender** ist zwischen-Gruppen-Variable und *within* bedeutet, dass **looks** und **personality** are Variablen mit wiederholten Messungen.

```
library(ez)
speedModel <- ezANOVA(data = speedData, dv = .(dateRating), wid = .(participant),
    between = .(gender), within = .(looks, personality), type = 3, detailed = TRUE)
```

```
## Warning: Converting "participant" to factor for ANOVA.

## Warning: Converting "gender" to factor for ANOVA.
```

```
speedModel
```

```
## $ANOVA
##                    Effect DFn DFd        SSn       SSd            F
## 1             (Intercept)   1  18 846249.800  760.2222 2.003690e+04
## 2                  gender   1  18      0.200  760.2222 4.735457e-03
## 3                   looks   2  36  20779.633  882.7111 4.237325e+02
## 5             personality   2  36  23233.600 1274.0444 3.282498e+02
## 4            gender:looks   2  36   3944.100  882.7111 8.042699e+01
## 6      gender:personality   2  36   4420.133 1274.0444 6.244868e+01
## 7       looks:personality   4  72   4055.267 1992.6222 3.663253e+01
## 8 gender:looks:personality   4  72   2669.667 1992.6222 2.411596e+01
##              p p<.05          ges
## 1 7.013239e-29     * 9.942319e-01
## 2 9.458958e-01       4.073486e-05
## 3 9.594812e-26     * 8.088849e-01
## 5 7.689430e-24     * 8.255493e-01
## 4 5.234187e-14     * 4.454748e-01
## 6 1.974986e-12     * 4.737685e-01
## 7 1.101308e-16     * 4.523510e-01
## 8 1.107801e-12     * 3.522328e-01
```

Factorielle ANOVA mit gemischtem Design II

```
##
## $`Mauchly's Test for Sphericity`
##                    Effect         W         p p<.05
## 3                   looks 0.9602054 0.7081010
## 4            gender:looks 0.9602054 0.7081010
## 5             personality 0.9293298 0.5363446
## 6      gender:personality 0.9293298 0.5363446
## 7       looks:personality 0.6133545 0.5339382
## 8 gender:looks:personality 0.6133545 0.5339382
##
## $`Sphericity Corrections`
##                    Effect       GGe        p[GG] p[GG]<.05       HFe
## 3                   looks 0.9617284 7.624114e-25         * 1.0744125
## 4            gender:looks 0.9617284 1.487026e-13         * 1.0744125
## 5             personality 0.9339944 2.056621e-22         * 1.0380537
## 6      gender:personality 0.9339944 9.442426e-12         * 1.0380537
## 7       looks:personality 0.7993543 9.003598e-14         * 0.9922411
## 8 gender:looks:personality 0.7993543 1.470422e-10         * 0.9922411
##          p[HF] p[HF]<.05
## 3 9.594812e-26         *
## 4 5.234187e-14         *
## 5 7.689430e-24         *
## 6 1.974986e-12         *
## 7 1.426883e-16         *
## 8 1.337876e-12         *
```

Factorielle ANOVA mit gemischtem Design als *glm*

Wir definieren neue (nicht orthogonale) Kontraste um z.B. die Vergleiche zu der Norm zu machen.

1. Kontrast vergleicht für **looks** *Attractive* mit *Average* (baseline = 0)
2. Kontrast vergleicht für **looks** *Ugly* mit *Average* (baseline = 0)

```
AttractivevsAv <- c(1, 0, 0)
UglyvsAv <- c(0, 0, 1)
contrasts(speedData$looks) <- cbind(AttractivevsAv, UglyvsAv)
```

Factorielle ANOVA mit gemischtem Design als *glm* (1)

1. Kontrast vergleicht für **personality** *Charismatic* mit *Average* (baseline = 0)
2. Kontrast vergleicht für **personality** *Dullard* mit *Average* (baseline = 0)

```
HighvsAv <- c(1, 0, 0)
DullvsAv <- c(0, 0, 1)
contrasts(speedData$personality) <- cbind(HighvsAv, DullvsAv)
```

(nicht orthogonale) Kontraste

```
attr(speedData$looks, "contrasts")
```

```
##              AttractivevsAv UglyvsAv
## Attractive                1        0
## Average                   0        0
## Ugly                      0        1
```

```
attr(speedData$personality, "contrasts")
```

```
##              HighvsAv DullvsAv
## Charismatic         1        0
## Average             0        0
## Dullard             0        1
```

Factorielle ANOVA mit gemischtem Design als *glm* (2)

```
baseline <- lme(dateRating ~ 1, random = ~1 | participant/looks/personality, data = speedData,
    method = "ML")
```

Sieht ähnlich aus wie faktorielle ANOVA mit wiederholten Messungen.

Factorielle ANOVA mit gemischtem Design als *glm* (2)

```r
baseline <- lme(dateRating ~ 1, random = ~1 | participant/looks/personality, data = speedData,
    method = "ML")
```

Sieht ähnlich aus wie faktorielle ANOVA mit wiederholten Messungen.

Weiter Faktoren werde hinzugefügt.

```r
looksM <- update(baseline, . ~ . + looks)
personalityM <- update(looksM, . ~ . + personality)
genderM <- update(personalityM, . ~ . + gender)
looks_gender <- update(genderM, . ~ . + looks:gender)
personality_gender <- update(looks_gender, . ~ . + personality:gender)
looks_personality <- update(personality_gender, . ~ . + looks:personality)
speedDateModel <- update(looks_personality, . ~ . + looks:personality:gender)
```

ANOVA-Tabelle I

```
anova(baseline, looksM, personalityM, genderM, looks_gender, personality_gender,
    looks_personality, speedDateModel)
```

```
##                    Model df      AIC      BIC    logLik   Test   L.Ratio
## baseline               1  5 1575.766 1591.730 -782.8829
## looksM                 2  7 1511.468 1533.819 -748.7343 1 vs 2  68.29719
## personalityM           3  9 1376.704 1405.441 -679.3520 2 vs 3 138.76442
## genderM                4 10 1378.702 1410.632 -679.3511 3 vs 4   0.00180
## looks_gender           5 12 1343.161 1381.477 -659.5808 4 vs 5  39.54079
## personality_gender     6 14 1289.198 1333.899 -630.5988 5 vs 6  57.96394
## looks_personality      7 18 1220.057 1277.530 -592.0283 6 vs 7  77.14102
## speedDateModel         8 22 1148.462 1218.707 -552.2309 7 vs 8  79.59473
##                    p-value
## baseline
## looksM              <.0001
## personalityM        <.0001
## genderM             0.9662
## looks_gender        <.0001
## personality_gender  <.0001
## looks_personality   <.0001
## speedDateModel      <.0001
```

```
summary(speedDateModel)
```

ANOVA-Tabelle II

```
## Linear mixed-effects model fit by maximum likelihood
##  Data: speedData
##        AIC      BIC    logLik
##   1148.462 1218.707 -552.2309
##
## Random effects:
##  Formula: ~1 | participant
##         (Intercept)
## StdDev:    1.158402
##
##  Formula: ~1 | looks %in% participant
##          (Intercept)
## StdDev: 0.0005251677
##
##  Formula: ~1 | personality %in% looks %in% participant
##         (Intercept)  Residual
## StdDev:    5.090892 0.1283062
##
## Fixed effects: dateRating ~ looks + personality + gender + looks:gender + personality:gender +      looks:personality + look
##                                                  Value Std.Error  DF  t-value
## (Intercept)                                       68.9  1.740866 108 39.57799
## looksAttractivevsAv                               18.2  2.400632  36  7.58134
## looksUglyvsAv                                    -17.7  2.400632  36 -7.37306
## personalityHighvsAv                               19.5  2.400632 108  8.12286
## personalityDullvsAv                              -21.9  2.400632 108 -9.12260
## genderMale                                         2.9  2.461957  18  1.17792
## looksAttractivevsAv:genderMale                    -1.5  3.395006  36 -0.44183
## looksUglyvsAv:genderMale                          -5.8  3.395006  36 -1.70839
## personalityHighvsAv:genderMale                    -8.5  3.395006 108 -2.50368
## personalityDullvsAv:genderMale                    -2.1  3.395006 108 -0.61856
## looksAttractivevsAv:personalityHighvsAv          -17.0  3.395006 108 -5.00736
## looksUglyvsAv:personalityHighvsAv                 16.0  3.395006 108  4.71280
## looksAttractivevsAv:personalityDullvsAv          -13.4  3.395006 108 -3.94697
## looksUglyvsAv:personalityDullvsAv                 16.8  3.395006 108  4.94845
## looksAttractivevsAv:personalityHighvsAv:genderMale  5.8  4.801263 108  1.20802
## looksUglyvsAv:personalityHighvsAv:genderMale     -18.5  4.801263 108 -3.85315
```

ANOVA-Tabelle III

```
## looksAttractivevsAv:personalityDullvsAv:genderMale  36.2  4.801263 108  7.53968
## looksUglyvsAv:personalityDullvsAv:genderMale         4.7  4.801263 108  0.97891
##                                                    p-value
## (Intercept)                                         0.0000
## looksAttractivevsAv                                 0.0000
## looksUglyvsAv                                       0.0000
## personalityHighvsAv                                 0.0000
## personalityDullvsAv                                 0.0000
## genderMale                                          0.2542
## looksAttractivevsAv:genderMale                      0.6613
## looksUglyvsAv:genderMale                            0.0962
## personalityHighvsAv:genderMale                      0.0138
## personalityDullvsAv:genderMale                      0.5375
## looksAttractivevsAv:personalityHighvsAv             0.0000
## looksUglyvsAv:personalityHighvsAv                   0.0000
## looksAttractivevsAv:personalityDullvsAv             0.0001
## looksUglyvsAv:personalityDullvsAv                   0.0000
## looksAttractivevsAv:personalityHighvsAv:genderMale  0.2297
## looksUglyvsAv:personalityHighvsAv:genderMale        0.0002
## looksAttractivevsAv:personalityDullvsAv:genderMale  0.0000
## looksUglyvsAv:personalityDullvsAv:genderMale        0.3298
##  Correlation:
##                                                    (Intr) lksAtA lksUgA prsnHA
## looksAttractivevsAv                                -0.689
## looksUglyvsAv                                      -0.689  0.500
## personalityHighvsAv                                -0.689  0.500  0.500
## personalityDullvsAv                                -0.689  0.500  0.500  0.500
## genderMale                                         -0.707  0.488  0.488  0.488
## looksAttractivevsAv:genderMale                      0.488 -0.707 -0.354 -0.354
## looksUglyvsAv:genderMale                            0.488 -0.354 -0.707 -0.354
## personalityHighvsAv:genderMale                      0.488 -0.354 -0.354 -0.707
## personalityDullvsAv:genderMale                      0.488 -0.354 -0.354 -0.354
## looksAttractivevsAv:personalityHighvsAv             0.488 -0.707 -0.354 -0.707
## looksUglyvsAv:personalityHighvsAv                   0.488 -0.354 -0.707 -0.707
## looksAttractivevsAv:personalityDullvsAv             0.488 -0.707 -0.354 -0.354
## looksUglyvsAv:personalityDullvsAv                   0.488 -0.354 -0.707 -0.354
```

ANOVA-Tabelle IV

```
## looksAttractivevsAv:personalityHighvsAv:genderMale -0.345  0.500  0.250  0.500
## looksUglyvsAv:personalityHighvsAv:genderMale       -0.345  0.250  0.500  0.500
## looksAttractivevsAv:personalityDullvsAv:genderMale -0.345  0.500  0.250  0.250
## looksUglyvsAv:personalityDullvsAv:genderMale       -0.345  0.250  0.500  0.250
##                                                    prsnDA gndrMl lkAA:M lkUA:M
## looksAttractivevsAv
## looksUglyvsAv
## personalityHighvsAv
## personalityDullvsAv
## genderMale                                          0.488
## looksAttractivevsAv:genderMale                     -0.354 -0.689
## looksUglyvsAv:genderMale                           -0.354 -0.689  0.500
## personalityHighvsAv:genderMale                     -0.354 -0.689  0.500  0.500
## personalityDullvsAv:genderMale                     -0.707 -0.689  0.500  0.500
## looksAttractivevsAv:personalityHighvsAv            -0.354 -0.345  0.500  0.250
## looksUglyvsAv:personalityHighvsAv                  -0.354 -0.345  0.250  0.500
## looksAttractivevsAv:personalityDullvsAv            -0.707 -0.345  0.500  0.250
## looksUglyvsAv:personalityDullvsAv                  -0.707 -0.345  0.250  0.500
## looksAttractivevsAv:personalityHighvsAv:genderMale  0.250  0.488 -0.707 -0.354
## looksUglyvsAv:personalityHighvsAv:genderMale        0.250  0.488 -0.354 -0.707
## looksAttractivevsAv:personalityDullvsAv:genderMale  0.500  0.488 -0.707 -0.354
## looksUglyvsAv:personalityDullvsAv:genderMale        0.500  0.488 -0.354 -0.707
##                                                    prHA:M prDA:M lkAA:HA
## looksAttractivevsAv
## looksUglyvsAv
## personalityHighvsAv
## personalityDullvsAv
## genderMale
## looksAttractivevsAv:genderMale
## looksUglyvsAv:genderMale
## personalityHighvsAv:genderMale
## personalityDullvsAv:genderMale                      0.500
## looksAttractivevsAv:personalityHighvsAv             0.500  0.250
## looksUglyvsAv:personalityHighvsAv                   0.500  0.250  0.500
## looksAttractivevsAv:personalityDullvsAv             0.250  0.500  0.500
## looksUglyvsAv:personalityDullvsAv                   0.250  0.500  0.250
```

ANOVA-Tabelle V

```
## looksAttractivevsAv:personalityHighvsAv:genderMale -0.707 -0.354 -0.707
## looksUglyvsAv:personalityHighvsAv:genderMale       -0.707 -0.354 -0.354
## looksAttractivevsAv:personalityDullvsAv:genderMale -0.354 -0.707 -0.354
## looksUglyvsAv:personalityDullvsAv:genderMale       -0.354 -0.707 -0.177
##                                                    lkUA:HA lkAA:DA lkUA:DA
## looksAttractivevsAv
## looksUglyvsAv
## personalityHighvsAv
## personalityDullvsAv
## genderMale
## looksAttractivevsAv:genderMale
## looksUglyvsAv:genderMale
## personalityHighvsAv:genderMale
## personalityDullvsAv:genderMale
## looksAttractivevsAv:personalityHighvsAv
## looksUglyvsAv:personalityHighvsAv
## looksAttractivevsAv:personalityDullvsAv             0.250
## looksUglyvsAv:personalityDullvsAv                   0.500   0.500
## looksAttractivevsAv:personalityHighvsAv:genderMale -0.354  -0.354  -0.177
## looksUglyvsAv:personalityHighvsAv:genderMale       -0.707  -0.177  -0.354
## looksAttractivevsAv:personalityDullvsAv:genderMale -0.177  -0.707  -0.354
## looksUglyvsAv:personalityDullvsAv:genderMale       -0.354  -0.354  -0.707
##                                                    lAA:HA: lUA:HA: lAA:DA:
## looksAttractivevsAv
## looksUglyvsAv
## personalityHighvsAv
## personalityDullvsAv
## genderMale
## looksAttractivevsAv:genderMale
## looksUglyvsAv:genderMale
## personalityHighvsAv:genderMale
## personalityDullvsAv:genderMale
## looksAttractivevsAv:personalityHighvsAv
## looksUglyvsAv:personalityHighvsAv
## looksAttractivevsAv:personalityDullvsAv
## looksUglyvsAv:personalityDullvsAv
```

ANOVA-Tabelle VI

```
## looksAttractivevsAv:personalityHighvsAv:genderMale
## looksUglyvsAv:personalityHighvsAv:genderMale        0.500
## looksAttractivevsAv:personalityDullvsAv:genderMale  0.500   0.250
## looksUglyvsAv:personalityDullvsAv:genderMale        0.250   0.500   0.500
##
## Standardized Within-Group Residuals:
##         Min          Q1         Med          Q3         Max
## -0.09479343 -0.01471239  0.00142862  0.01218635  0.05289021
##
## Number of Observations: 180
## Number of Groups:
##                           participant                   looks %in% participant
##                                    20                                       60
## personality %in% looks %in% participant
##                                    180
```

Haupteffekt von **gender**

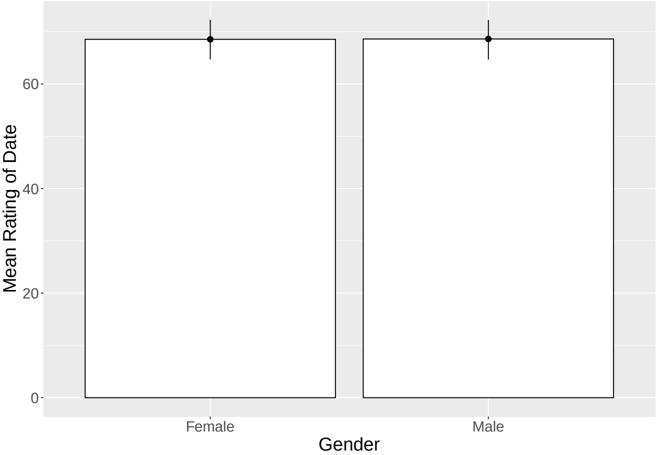

Figure 6: Haupteffekt von gender.

Haupteffekt von **looks**

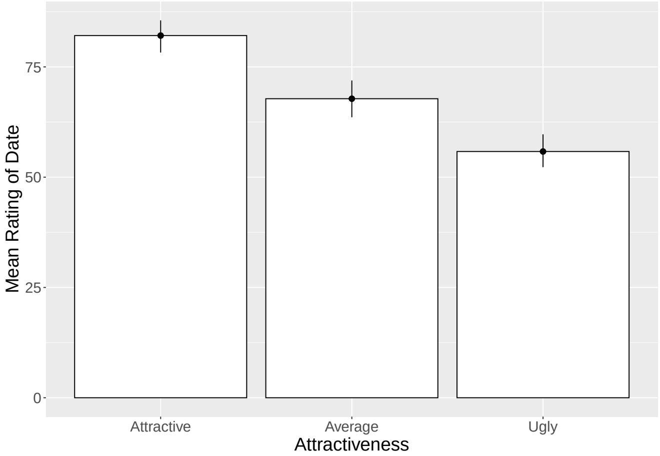

Figure 7: Haupteffekt von looks.

Haupeffekt von **personality**

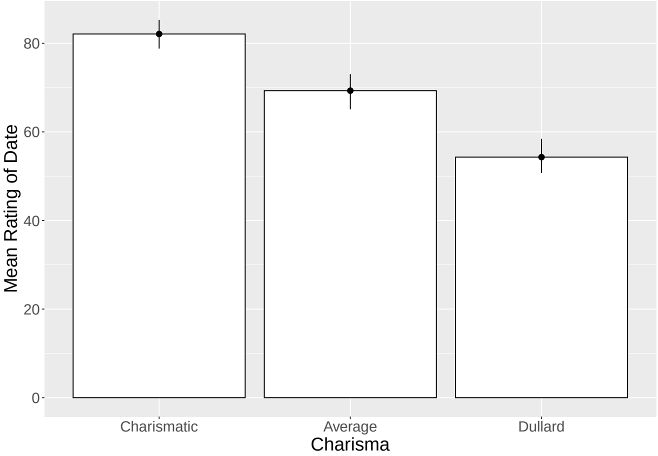

Figure 8: Haupteffekt von personality.

Wechselwirkung **looks**×**gender**

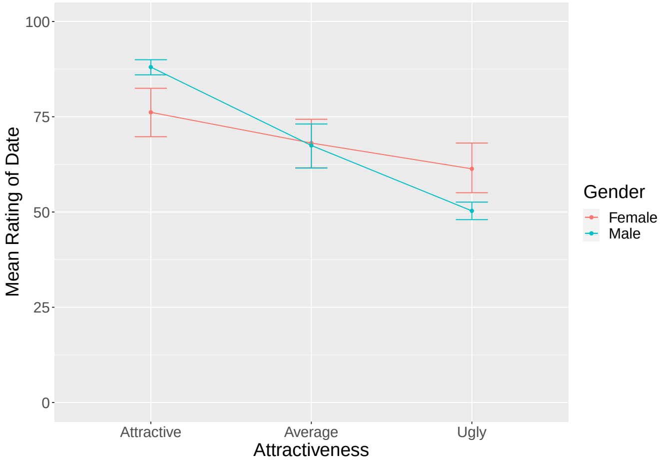

Figure 9: Wechselwirkung zwischen looks und gender.

Wechselwirkung **personality**×**gender**

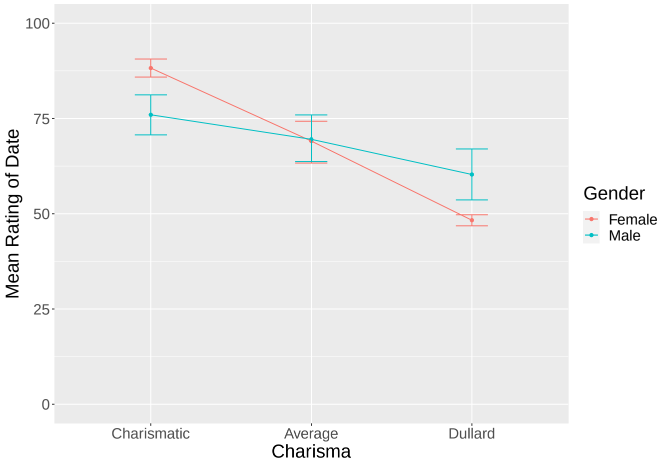

Figure 10: Wechselwirkung looks*imes*gender. Frauen sind mehr von Charisma beeinflusst als Männer.

Wechselwirkung **looks**×**personality**

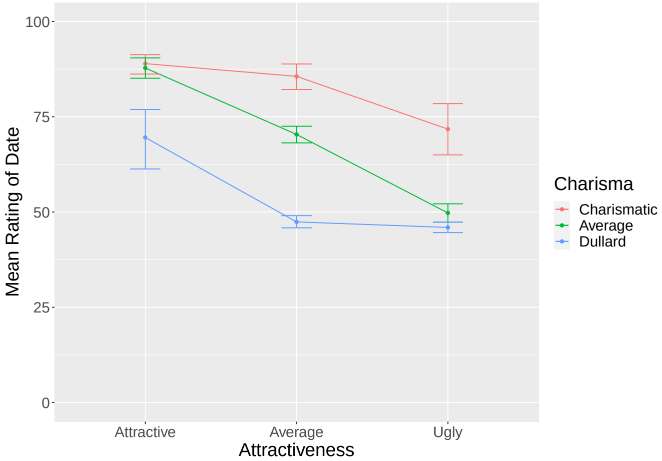

Figure 11: Wechselwirkung zwischen looks und personality.

Wechselwirkung **looks**×**personality**×**gender**

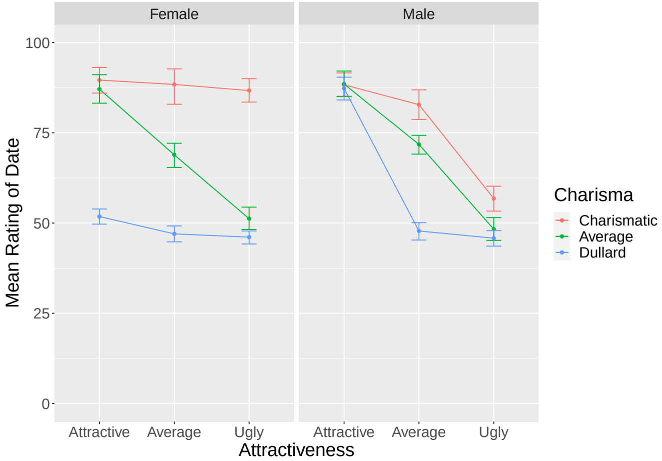

Figure 12: Wechselwirkung zwischen looks, personality und gender