

Biostatistics I: Linear Regression

Linear Regression in R

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Linear Regression in R

To fit a **linear regression model** in  we use the function **lm()**.

```
lm(formula, data, subset, weights, na.action,  
  model = TRUE, x = FALSE, y = FALSE,  
  contrasts = NULL, offset, ...)
```

The most important arguments of lm() are

- **formula:**
a formula object
- **data:**
`data.frame` (optional, but usually needed)

Model Formula

A **formula** object has the form

```
response ~ terms
```

for example

```
y ~ x1 + x2 + x3
```

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```
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```

for example

```
y ~ x1 + x2 + x3
```

- Variables are separated by "+" signs.
- An **intercept** is automatically included.
- **One-sided formulas** (omitting the outcome) are possible.

Model Formula

The **intercept** can be removed from a formula by using "**-1**" or "**+0**", i.e.,

```
y ~ x1 + x2 - 1  
y ~ x1 + x2 + 0
```

Model Formula

The **intercept** can be removed from a formula by using "**-1**" or "**+0**", i.e.,

```
y ~ x1 + x2 - 1  
y ~ x1 + x2 + 0
```

Include all (other) variables as covariates using ".":

```
y ~ .
```

Model Formula

The **intercept** can be removed from a formula by using "**-1**" or "**+0**", i.e.,

```
y ~ x1 + x2 - 1  
y ~ x1 + x2 + 0
```

Include all (other) variables as covariates using ".":

```
y ~ .
```

Remove terms from the model using "**-**", e.g.:

```
y ~ . - x4
```

Model Formula

Example

If we had a data.frame like this:

y	x1	x2	x3	x4	x5
-1.01	-1.54	0.96	0.60	0.25	0.94
0.11	0.70	0.39	0.22	1.24	0.20
0.93	0.42	0.69	-0.59	0.28	-1.79
0.77	1.01	-0.19	-0.95	0.82	-0.53
-1.20	-0.66	-1.32	0.02	-0.21	0.08

Within lm(), the formula specified by

```
y ~ .
```

is identical to the formula

```
y ~ x1 + x2 + x3 + x4 + x5
```

Model Formula

Example

If we had a data.frame like this:

y	x1	x2	x3	x4	x5
-1.01	-1.54	0.96	0.60	0.25	0.94
0.11	0.70	0.39	0.22	1.24	0.20
0.93	0.42	0.69	-0.59	0.28	-1.79
0.77	1.01	-0.19	-0.95	0.82	-0.53
-1.20	-0.66	-1.32	0.02	-0.21	0.08

Within lm(), the formula specified by

```
y ~ .
```

is identical to the formula

```
y ~ x1 + x2 + x3 + x4 + x5
```

and the formula specified by

```
y ~ . - x3
```

is identical to the formula

```
y ~ x1 + x2 + x4 + x5
```

Algebraic Operations

Example: We would like to have the sum of **x2** and **x3** as a covariate.

Instead of pre-calculating this new variable

```
z <- x2 + x3  
y ~ x1 + z
```

Algebraic Operations

Example: We would like to have the sum of **x2** and **x3** as a covariate.

Instead of pre-calculating this new variable

```
z <- x2 + x3  
y ~ x1 + z
```

we can include this calculation directly in the model formula:

```
y ~ x1 + I(x2 + x3)
```

The function **I()** indicates **algebraic operations**,

Algebraic Operations

Example: We would like to have the sum of **x2** and **x3** as a covariate.

Instead of pre-calculating this new variable

```
z <- x2 + x3  
y ~ x1 + z
```

we can include this calculation directly in the model formula:

```
y ~ x1 + I(x2 + x3)
```

The function **I()** indicates **algebraic operations**,

e.g., to distinguish the sum **x2 + x3** from the formula including the separate variables:

```
y ~ x1 + x2 + x3
```

A First Linear Regression

```
model1 <- lm(SBP ~ age + gender, data = nhanes)

model1

##
## Call:
## lm(formula = SBP ~ age + gender, data = nhanes)
##
## Coefficients:
## (Intercept)      age   genderfemale
##       106.097     0.365      -5.763
```

Model Summary

```
summary(model1)

##
## Call:
## lm(formula = SBP ~ age + gender, data = nhanes)
##
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -35.37   -9.08   -1.95    7.85   53.30 
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 106.0969    3.2456   32.69 < 2e-16 ***
## age          0.3646    0.0715    5.10  8.4e-07 ***
## genderfemale -5.7627    2.1531   -2.68   0.0081 ** 
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 14.3 on 183 degrees of freedom
## Multiple R-squared:  0.136,    Adjusted R-squared:  0.127 
## F-statistic: 14.5 on 2 and 183 DF,  p-value: 1.49e-06
```

Elements of a Fitted Model

The fitted object `model1` is an object of class "`lm`":

```
class(model1)
```

```
## [1] "lm"
```

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class(model1)
```

```
## [1] "lm"
```

Such an object has the underlying structure of a `list` object:

```
str(model1)
```

```
## List of 13
## $ coefficients : Named num [1:3] 106.097 0.365 -5.763
##   ..- attr(*, "names")= chr [1:3] "(Intercept)" "age" "genderfemale"
## $ residuals     : Named num [1:186] -10.86 -14.62 -18.77 -8.48 -6.01 ...
##   ..- attr(*, "names")= chr [1:186] "10" "14" "41" "77" ...
## $ effects       : Named num [1:186] -1626.98 66.9 38.4 -7.19 -6.27 ...
##   ..- attr(*, "names")= chr [1:186] "(Intercept)" "age" "genderfemale" "" ...
## $ rank          : int 3
## $ fitted.values: Named num [1:186] 119 120 129 114 121 ...
##   ..- attr(*, "names")= chr [1:186] "10" "14" "41" "77" ...
## [ ... ]
```

Elements of a Fitted Model

```
names(model1)

## [1] "coefficients"    "residuals"        "effects"          "rank"
## [5] "fitted.values"   "assign"           "qr"              "df.residual"
## [9] "contrasts"       "xlevels"          "call"             "terms"
## [13] "model"
```

Elements of a Fitted Model

```
names(model1)
```

```
## [1] "coefficients"   "residuals"      "effects"        "rank"  
## [5] "fitted.values"  "assign"         "qr"             "df.residual"  
## [9] "contrasts"       "xlevels"        "call"           "terms"  
## [13] "model"
```

We can access the separate elements either with the `$` operator, or using `[[[]]]`.

```
model1$coefficients
```

```
## (Intercept)      age  genderfemale  
##    106.0969     0.3646     -5.7627
```

Elements of a Fitted Model

coefficients	a named vector of coefficients	$\hat{\beta}$
residuals	the residuals	$\hat{\varepsilon}$
fitted.values	the fitted mean values	\hat{y}
rank	the numeric rank of the fitted linear model	usually: $p + 1$
weights	the specified weights (only for weighted fits)	
df.residual	the residual degrees of freedom	$n - p - 1$
call	the matched call	
terms	the terms object used	
contrasts	the contrasts used (only where relevant)	
xlevels	levels of the factor covariates (only where relevant)	
offset	the offset used (missing if none were used)	
y	the response used (if requested)	y
x	the model matrix used (if requested)	design matrix X
model	if requested (the default), the model frame used	
na.action	information returned by <code>model.frame</code> on the handling of NAs (where relevant)	

Model Rank

The column **rank** is number of **linearly independent** columns in a matrix.

The new variable `age_half` is a linear combination of `age`:

```
nhanes$age_half <- nhanes$age/2
```

⇒ **Rank-deficient model:**

```
lm_rank_def <- lm(SBP ~ age + age_half + gender, data = nhanes, x = TRUE)
```

Model Rank

The column **rank** is number of **linearly independent** columns in a matrix.

The new variable `age_half` is a linear combination of `age`:

```
nhanes$age_half <- nhanes$age/2
```

⇒ **Rank-deficient model:**

```
lm_rank_def <- lm(SBP ~ age + age_half + gender, data = nhanes, x = TRUE)
```

```
head(lm_rank_def$x, 3) # design matrix
```

```
##      (Intercept) age age_half genderfemale
## 10          1    35     17.5         0
## 14          1    38     19.0         0
## 41          1    78     39.0         1
```

```
ncol(lm_rank_def$x) # number of columns
```

```
## [1] 4
## lm_rank_def$rank # rank
## [1] 3
```

Model Rank

The least squares estimator **requires full rank**.

⇒ It is not possible to estimate parameters of linearly dependent variables:

```
lm_rank_def  
  
##  
## Call:  
## lm(formula = SBP ~ age + age_half + gender, data = nhanes, x = TRUE)  
##  
## Coefficients:  
## (Intercept)           age      age_half  genderfemale  
##       106.097        0.365          NA         -5.763
```

df.residual, call & xlevels

Residual degrees of freedom: $n - p - 1$

```
model1$df.residual
```

```
## [1] 183
```

```
nrow(model1$model) - length(model1$coef)
```

```
## [1] 183
```

df.residual, call & xlevels

Residual degrees of freedom: $n - p - 1$

```
model1$df.residual          nrow(model1$model) - length(model1$coef)  
## [1] 183                      ## [1] 183
```

Function call:

```
model1$call  
## lm(formula = SBP ~ age + gender, data = nhanes)
```

Levels of factor covariates:

```
model1$xlevels  
## $gender  
## [1] "male"    "female"
```

Additional Arguments

`lm()` has several more (optional) arguments:

- **subset**:
a logical vector specifying which observations should be used
- **weights**:
a numeric vector of weights for weighted least squares
- **na.action**:
a character string indicating how missing values should be handled
- **contrasts**:
a list specifying contrasts for categorical covariates
- **offset**:
a numeric vector or matrix

Subsets

Fit a model on a subset of the data:

```
lm_sub <- lm(SBP ~ age + gender, data = nhanes, subset = educ == "low")
```

Subsets

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```
lm_sub <- lm(SBP ~ age + gender, data = nhanes, subset = educ == "low")
```

original data:

```
nrow(nhanes)
```

```
## [1] 186
```

design matrix:

```
nrow(lm_sub$model)
```

```
## [1] 70
```

same as with `subset()`:

```
nrow(subset(nhanes, educ == "low"))
```

```
## [1] 70
```

Subsets

Fit a model on a subset of the data:

```
lm_sub <- lm(SBP ~ age + gender, data = nhanes, subset = educ == "low")
```

original data:

```
nrow(nhanes)
```

```
## [1] 186
```

design matrix:

```
nrow(lm_sub$model)
```

```
## [1] 70
```

same as with `subset()`:

```
nrow(subset(nhanes, educ == "low"))
```

```
## [1] 70
```

Use of multiple criteria:

```
lm_sub2 <- lm(SBP ~ age + gender, data = nhanes,
               subset = educ == "low" & age < 60)
```

Weights: Weighted Least Squares

Assumption of the **OLS**: $\text{var}(\varepsilon_i) = \sigma^2$

⇒ **Weighted least squares**: $\sum_{i=1}^n w_i \hat{\varepsilon}_i^2 \rightarrow \min_{\beta}$,

with weights w_i inversely proportional to the variances $\text{var}(\varepsilon_i)$.

Weights: Weighted Least Squares

Assumption of the **OLS**: $\text{var}(\varepsilon_i) = \sigma^2$

⇒ **Weighted least squares**: $\sum_{i=1}^n w_i \hat{\varepsilon}_i^2 \rightarrow \min_{\beta}$,

with weights w_i inversely proportional to the variances $\text{var}(\varepsilon_i)$.

(here: assumption variance associated with age)

```
lm_WLS <- lm(SBP ~ age + gender, weights = 1/age, data = nhanes)  
lm_WLS$weights  
  
## [1] 0.02857 0.02632 0.01282 0.04348 0.02500 0.01852 0.03226 0.03704 0.02703  
## [10] 0.02000 0.01587 0.03846 0.02857 0.02273 0.02941 0.01667 0.04167 0.02083  
## [...]
```

Missing Values

```
model2 <- lm(SBP ~ age + gender + alc, data = nhanes)
summary(model2)

## [ ... ]
##
## Residual standard error: 13.8 on 148 degrees of freedom
##   (34 observations deleted due to missingness)
## Multiple R-squared:  0.182,   Adjusted R-squared:  0.165
## F-statistic: 10.9 on 3 and 148 DF,  p-value: 1.56e-06
```

Missing Values

```
model2 <- lm(SBP ~ age + gender + alc, data = nhanes)
summary(model2)

## [ ... ]
##
## Residual standard error: 13.8 on 148 degrees of freedom
##   (34 observations deleted due to missingness)
## Multiple R-squared:  0.182,   Adjusted R-squared:  0.165
## F-statistic: 10.9 on 3 and 148 DF,  p-value: 1.56e-06
```

Global option:

```
getOption("na.action")

## [1] "na.omit"
```

Missing Values

Trying to fit a model with **missing values** results in an **error**:

```
lm(SBP ~ age + gender + alc, data = nhanes, na.action = NULL)
```

```
## Error in lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...): NA/Nan/Inf  
in 'x'
```

```
lm(SBP ~ age + gender + alc, data = nhanes, na.action = "na.pass")
```

```
## Error in lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...): NA/Nan/Inf  
in 'x'
```

Missing Values

Trying to fit a model with **missing values** results in an **error**:

```
lm(SBP ~ age + gender + alc, data = nhanes, na.action = NULL)
```

```
## Error in lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...): NA/Nan/Inf  
in 'x'
```

```
lm(SBP ~ age + gender + alc, data = nhanes, na.action = "na.pass")
```

```
## Error in lm.fit(x, y, offset = offset, singular.ok = singular.ok, ...): NA/Nan/Inf  
in 'x'
```

na.fail gives a similar error:

```
lm(SBP ~ age + gender + alc, data = nhanes, na.action = "na.fail")
```

```
## Error in na.fail.default(structure(list(SBP = c(108, 105.333333333333, : missing  
values in object
```

Missing Values

The options **na.omit** and **na.exclude** will remove rows with missing values:

```
model2.omit <- lm(SBP ~ age + gender + alc, data = nhanes, na.action = "na.omit")
model2.exclude <- lm(SBP ~ age + gender + alc, data = nhanes,
                      na.action = "na.exclude")
```

There is a relevant difference when we use functions like

- **residuals()**
- **predict()**

```
head(residuals(model2.omit))
```

```
##      14       41       77       91      105      149
## -12.006 -17.001 -12.860 -3.394  9.295 -9.242
```

```
head(residuals(model2.exclude))
```

```
##      10       14       41       77       91      105
##       NA -12.006 -17.001 -12.860 -3.394  9.295
```

Contrasts

When categorical variables are coded as **factor**,  applies contrasts.

```
lm(SBP ~ age + gender + smoke, data = nhanes)

##
## Call:
## lm(formula = SBP ~ age + gender + smoke, data = nhanes)
##
## Coefficients:
##   (Intercept)          age  genderfemale      smoke.L      smoke.Q
##     102.661       0.446      -8.011      -1.752       4.723
```

Contrasts

When categorical variables are coded as **factor**, R applies contrasts.

```
lm(SBP ~ age + gender + smoke, data = nhanes)

##
## Call:
## lm(formula = SBP ~ age + gender + smoke, data = nhanes)
##
## Coefficients:
##   (Intercept)           age   genderfemale       smoke.L       smoke.Q
##     102.661        0.446      -8.011       -1.752        4.723
```

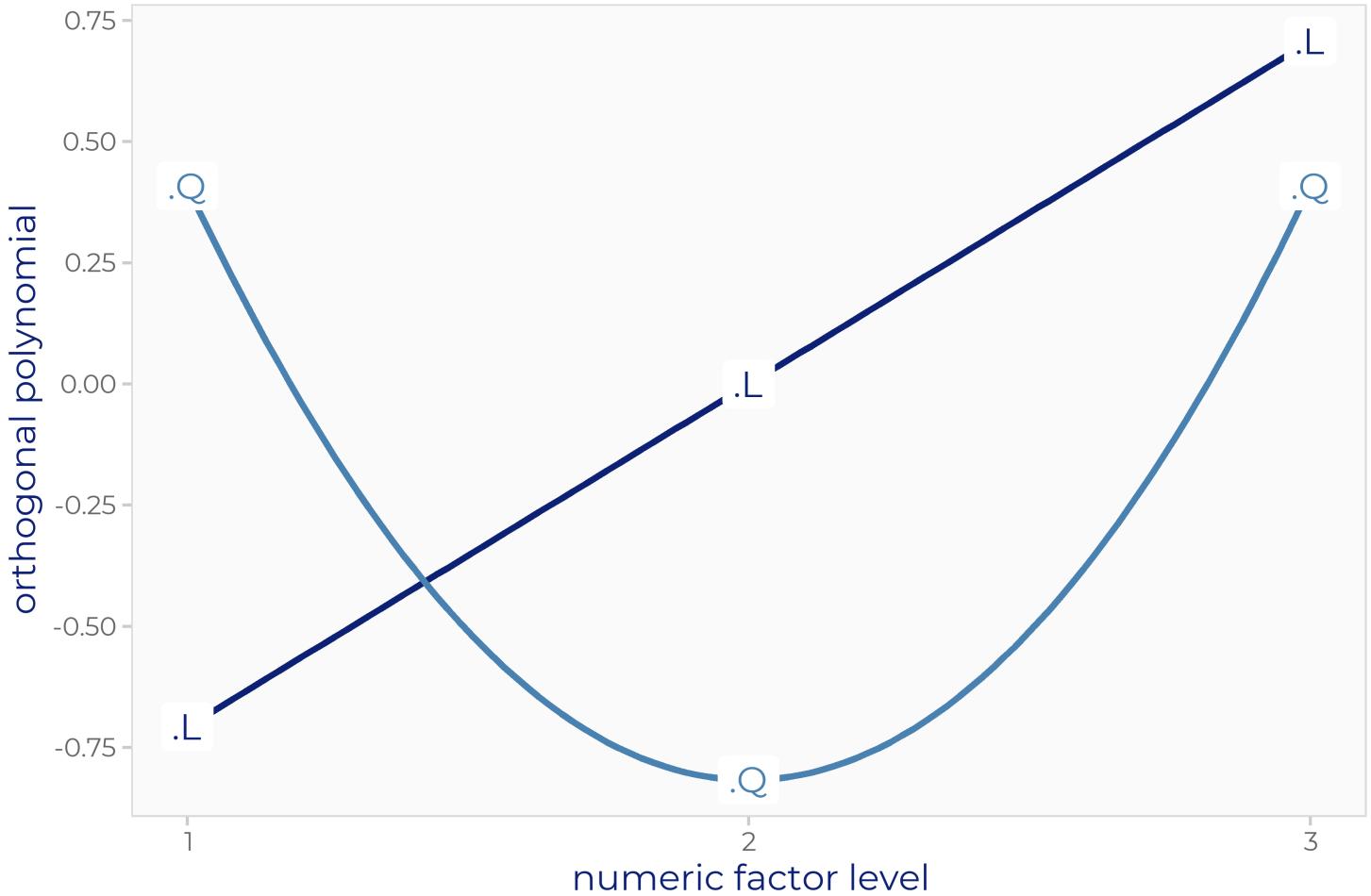
```
contrasts(nhanes$smoke)
```

```
##          .L      .Q
## [1,] -7.071e-01  0.4082
## [2,] -7.850e-17 -0.8165
## [3,]  7.071e-01  0.4082
```

Orthogonal Polynomials

```
round(contr.poly(3), 3)
```

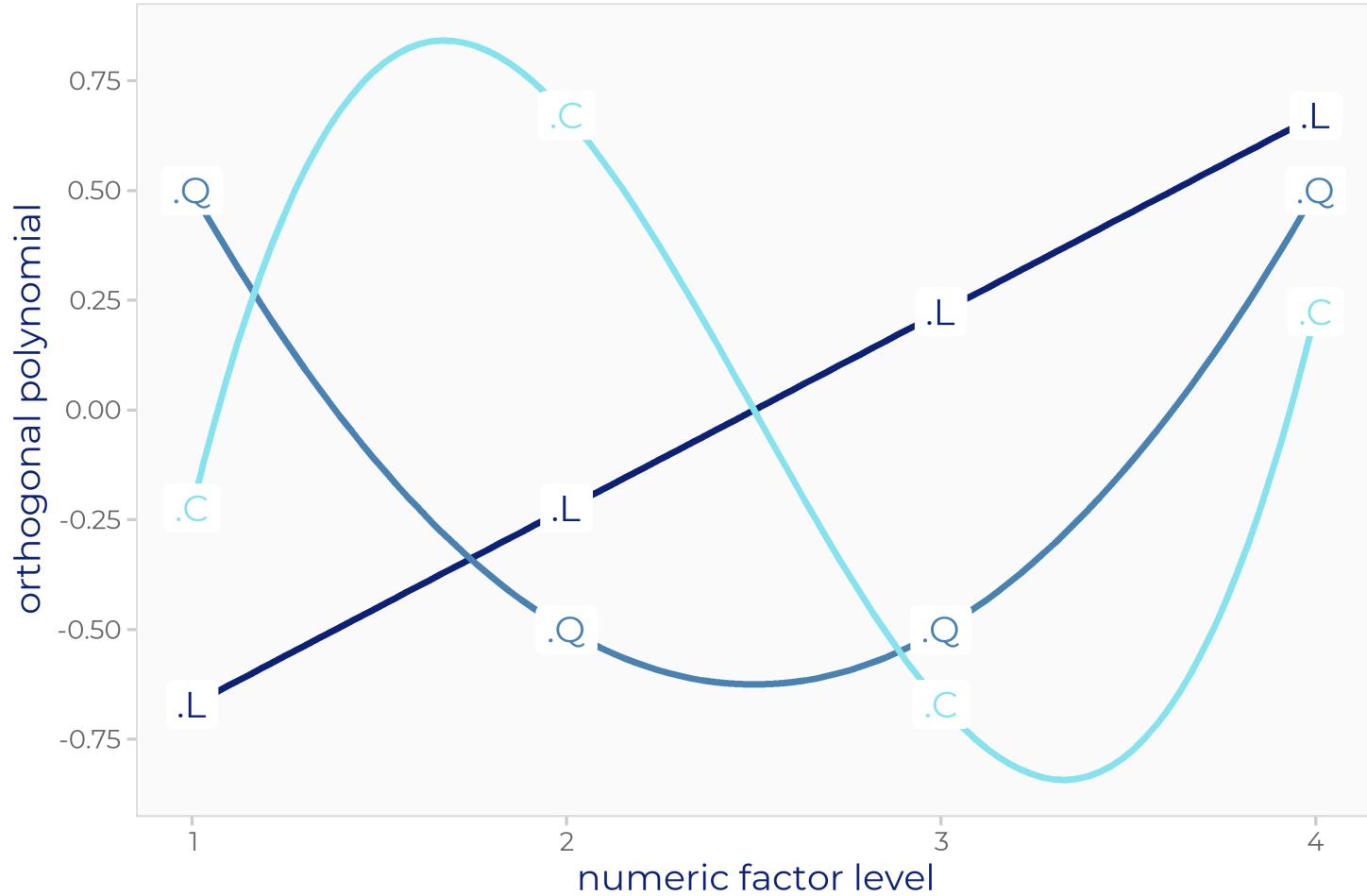
```
##          .L      .Q
## [1,] -0.707  0.408
## [2,]  0.000 -0.816
## [3,]  0.707  0.408
```



Orthogonal Polynomials

```
round(contr.poly(4), 3)
```

```
##          .L      .Q      .C
## [1,] -0.671  0.5 -0.224
## [2,] -0.224 -0.5  0.671
## [3,]  0.224 -0.5 -0.671
## [4,]  0.671  0.5  0.224
```



Contrasts

Global Option:

```
getOption("contrasts")  
  
##          unordered      ordered  
## "contr.treatment"    "contr.poly"
```

Contrasts

Global Option:

```
getOption("contrasts")  
  
##          unordered      ordered  
## "contr.treatment"    "contr.poly"
```

Dummy Coding:

```
contr.treatment(c("A", "B", "C"))  
  
##   B C  
## A 0 0  
## B 1 0  
## C 0 1
```

Effect Coding:

```
contr.sum(c("A", "B", "C"))  
  
## [,1] [,2]  
## A     1     0  
## B     0     1  
## C    -1    -1
```

Contrasts

```
lm(SBP ~ age + gender + smoke + occup, data = nhanes,
  contrasts = list(smoke = "contr.treatment",
                    occup = "contr.sum"))

##  
## Call:  
## lm(formula = SBP ~ age + gender + smoke + occup, data = nhanes,  
##       contrasts = list(smoke = "contr.treatment", occup = "contr.sum"))  
##  
## Coefficients:  
## (Intercept)           age   genderfemale   smokeformer   smokecurrent  
##      108.645        0.398      -8.175        -7.590        -1.992  
## occup1            occup2  
##     -0.942        2.581
```