

# A Tutorial on fitting Cumulative Link Models with the **ordinal** Package

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## Abstract

It is shown by example how a cumulative link mixed model is fitted with the `clm` function in package **ordinal**. Model interpretation and inference is briefly discussed.

We will consider the data on the bitterness of wine from Randall (1989) presented in Table 1 and available as the object `wine` in package **ordinal**. The data were also analyzed with mixed effects models by Tutz and Hennevogl (1996). The following gives an impression of the wine data object:

```
> data(wine)
> head(wine)

  response rating temp contact bottle judge
1       36      2 cold      no       1     1
2       48      3 cold      no       2     1
3       47      3 cold     yes       3     1
4       67      4 cold     yes       4     1
5       77      4 warm      no       5     1
6       60      4 warm      no       6     1

> str(wine)

'data.frame':      72 obs. of  6 variables:
 $ response: num  36 48 47 67 77 60 83 90 17 22 ...
 $ rating  : Ord.factor w/ 5 levels "1"<"2"<"3"<"4"<...: 2 3 3 4 4 4 5 5 1 2 ...
 $ temp    : Factor w/ 2 levels "cold","warm": 1 1 1 1 2 2 2 2 1 1 ...
 $ contact : Factor w/ 2 levels "no","yes": 1 1 2 2 1 1 2 2 1 1 ...
 $ bottle  : Factor w/ 8 levels "1","2","3","4",...: 1 2 3 4 5 6 7 8 1 2 ...
 $ judge   : Factor w/ 9 levels "1","2","3","4",...: 1 1 1 1 1 1 1 1 2 2 ...
```

The data represent a factorial experiment on factors determining the bitterness of wine with 1 = “least bitter” and 5 = “most bitter”. Two treatment factors (temperature and contact) each have two levels. Temperature and contact between juice and skins can be controlled when crushing grapes during wine production. Nine judges each assessed wine from two bottles from each of the four treatment conditions, hence there are 72 observations in all. For more information see the manual entry for the wine data: `help(wine)`.

We will fit the following cumulative link mixed model to the wine data:

$$\text{logit}(P(Y_i \leq j)) = \theta_j - \beta_1(\text{temp}_i) - \beta_2(\text{contact}_i) \quad (1)$$
$$i = 1, \dots, n, \quad j = 1, \dots, J - 1$$

Table 1: Ratings of the bitterness of some white wines. Data are adopted from Randall (1989).

Temperature	Contact	Bottle	Judge								
			1	2	3	4	5	6	7	8	9
cold	no	1	2	1	2	3	2	3	1	2	1
cold	no	2	3	2	3	2	3	2	1	2	2
cold	yes	3	3	1	3	3	4	3	2	2	3
cold	yes	4	4	3	2	2	3	2	2	3	2
warm	no	5	4	2	5	3	3	2	2	3	3
warm	no	6	4	3	5	2	3	4	3	3	2
warm	yes	7	5	5	4	5	3	5	2	3	4
warm	yes	8	5	4	4	3	3	4	3	4	4

This is a model for the cumulative probability of the  $i$ th rating falling in the  $j$ th category or below, where  $i$  index all observations and  $j = 1, \dots, J$  index the response categories ( $J = 5$ ).  $\{\theta_j\}$  are known as threshold parameters or cut-points.

We fit this cumulative link model by maximum likelihood with the `clm` function in package `ordinal`. Here we save the fitted `clm` model in the object `fm1` (short for fitted model 1) and print the model by simply typing its name:

```
> fm1 <- clm(rating ~ temp + contact, data = wine)
> fm1

formula: rating ~ temp + contact
data:    wine

link threshold nobs logLik AIC      niter max.grad
logit flexible  72   -86.49 184.98 6(0)  4.01e-12

Coefficients:
  tempwarm contactyes
    2.503      1.528

Threshold coefficients:
  1|2   2|3   3|4   4|5
-1.344 1.251 3.467 5.006

Additional information is provided with the summary method:
> summary(fm1)

formula: rating ~ temp + contact
data:    wine

link threshold nobs logLik AIC      niter max.grad cond.H
logit flexible  72   -86.49 184.98 6(0)  4.01e-12 2.7e+01

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
tempwarm      2.5031      0.5287   4.735 2.19e-06 ***
contactyes    1.5278      0.4766   3.205 0.00135 **
---

```

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Threshold coefficients:

	Estimate	Std. Error	z value
1 2	-1.3444	0.5171	-2.600
2 3	1.2508	0.4379	2.857
3 4	3.4669	0.5978	5.800
4 5	5.0064	0.7309	6.850

The primary result is the coefficient table with parameter estimates, standard errors and Wald (or normal) based  $p$ -values for tests of the parameters being zero. The maximum likelihood estimates of the parameters are:

$$\hat{\beta}_1 = 2.50, \hat{\beta}_2 = 1.53, \{\hat{\theta}_j\} = [-1.34, 1.25, 3.47, 5.01]. \quad (2)$$

The condition number of the Hessian measures the empirical identifiability of the model. High numbers, say larger than  $10^4$  or  $10^6$  indicate that the model is ill defined. This would indicate that the model can be simplified, that possibly some parameters are not identifiable, and that optimization of the model can be difficult. In this case the condition number of the Hessian does not indicate a problem with the model.

The coefficients for **temp** and **contact** are positive indicating that higher temperature and more contact increase the bitterness of wine, i.e., rating in higher categories is more likely. The odds ratio of the event  $Y \geq j$  is  $\exp(\beta_{\text{treatment}})$ , thus the odds ratio of bitterness being rated in category  $j$  or above at warm relative to cold temperatures is

```
> exp(coef(fm1)[5])
```

```
tempwarm
12.22034
```

The  $p$ -values for the location coefficients provided by the **summary** method are based on the so-called Wald statistic. More accurate test are provided by likelihood ratio tests. These can be obtained with the **anova** method, for example, the likelihood ratio test of **contact** is

```
> fm2 <- clm(rating ~ temp, data = wine)
> anova(fm2, fm1)
```

Likelihood ratio tests of cumulative link models:

	formula:	link: threshold:
fm2	rating ~ temp	logit flexible
fm1	rating ~ temp + contact	logit flexible

  

	no.par	AIC	logLik	LR.stat	df	Pr(>Chisq)
fm2	5	194.03	-92.013			
fm1	6	184.98	-86.492	11.043	1	0.0008902 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

which in this case produce a slightly lower  $p$ -value. Equivalently we can use **drop1** to obtain likelihood ratio tests of the explanatory variables while *controlling* for the remaining variables:

```
> drop1(fm1, test = "Chi")
```

Single term deletions

```
Model:
rating ~ temp + contact
      Df    AIC    LRT   Pr(Chi)
<none>    184.98
temp      1 209.91 26.928 2.112e-07 ***
contact   1 194.03 11.043 0.0008902 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Likelihood ratio tests of the explanatory variables while *ignoring* the remaining variables are provided by the `add1` method:

```
> fm0 <- clm(rating ~ 1, data = wine)
> add1(fm0, scope = ~temp + contact, test = "Chi")
```

Single term additions

```
Model:
rating ~ 1
      Df    AIC    LRT   Pr(Chi)
<none>    215.44
temp      1 194.03 23.4113 1.308e-06 ***
contact   1 209.91  7.5263  0.00608 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

In this case these latter tests are not as strong as the tests controlling for the other variable.

Confidence intervals are provided by the `confint` method:

```
> confint(fm1)

                2.5 %    97.5 %
tempwarm      1.5097627 3.595225
contactyes    0.6157925 2.492404
```

These are based on the profile likelihood function and generally fairly accurate. Less accurate, but simple and symmetric confidence intervals based on the standard errors of the parameters (so-called Wald confidence intervals) can be obtained with

```
> confint.default(fm1)

                2.5 %    97.5 %
1|2          -2.3578848 -0.330882
2|3           0.3925794  2.109038
3|4           2.2952980  4.638476
4|5           3.5738541  6.438954
tempwarm      1.4669081  3.539296
contactyes    0.5936345  2.461961
```

The cumulative link model in (1) assume that the thresholds,  $\{\theta_j\}$  are constant for all values of the remaining explanatory variables, here `temp` and `contact`. This is generally referred to as the *proportional odds assumption* or *equal slopes assumption*, while both names are not entirely adequate since the assumption is also made for other links than the logit and for categorical variables as well as continuous ones. We can relax that assumption in two general ways: with nominal effects and scale effects which we will now discuss in turn:

Nominal effects:

The CLM in (1) specifies a structure in which the regression parameters,  $\beta$  are not allowed to vary with  $j$  alongas are the threshold parameters,  $\theta$ . Nominal effects relax this assumption by allowing one or more regression parameters to vary with  $j$ . In the following model we allow the regression parameter for **contact** to vary with  $j$ :

$$\text{logit}(P(Y_i \leq j)) = \theta_j - \beta_1(\text{temp}_i) - \beta_{2j}(\text{contact}_i) \quad (3)$$

$$i = 1, \dots, n, \quad j = 1, \dots, J - 1$$

This means that there is one estimate of  $\beta_2$  for each  $j$ , i.e., for each of the five thresholds in addition to the estimates of  $\theta_j$  for each  $j$ . This model is specified as follows in `clm`:

```
> fm.nom <- clm(rating ~ temp, nominal = ~contact, data = wine)
> summary(fm.nom)
```

```
formula: rating ~ temp
nominal: ~contact
data: wine
```

```
link threshold nobs logLik AIC niter max.grad cond.H
logit flexible 72 -86.21 190.42 6(0) 1.64e-10 4.8e+01
```

Coefficients:

```
Estimate Std. Error z value Pr(>|z|)
tempwarm 2.519 0.535 4.708 2.5e-06 ***
---
```

```
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Threshold coefficients:

```
Estimate Std. Error z value
1|2.(Intercept) -1.3230 0.5623 -2.353
2|3.(Intercept) 1.2464 0.4748 2.625
3|4.(Intercept) 3.5500 0.6560 5.411
4|5.(Intercept) 4.6602 0.8604 5.416
1|2.contactyes -1.6151 1.1618 -1.390
2|3.contactyes -1.5116 0.5906 -2.559
3|4.contactyes -1.6748 0.6488 -2.581
4|5.contactyes -1.0506 0.8965 -1.172
```

As can be seen from the output of `summary` there is no regression coefficient estimated for **contact**, but there are two sets of threshold parameters estimated.

The first five threshold parameters have `.(Intercept)` appended their names indicating that these are the estimates of  $\theta_j$ . The following five threshold parameters have `.contactyes` appended their name indicating that these parameters are differences between the threshold parameters at the two levels of contact. This interpretation corresponds to the default treatment contrasts; if other types of contrasts are specified, the interpretation is a little different.

We can perform a likelihood ratio test of the equal slopes or proportional odds assumption for **contact** by comparing the likelihoods of models (1) and (7) as follows:

```
> anova(fm1, fm.nom)
```

Likelihood ratio tests of cumulative link models:

```

      formula:          nominal: link: threshold:
fm1   rating ~ temp + contact ~1      logit flexible
fm.nom rating ~ temp          ~contact logit flexible

```

```

      no.par   AIC  logLik LR.stat df Pr(>Chisq)
fm1          6 184.98 -86.492
fm.nom       9 190.42 -86.209  0.5667  3      0.904

```

There is only little difference in the log-likelihoods of the two models, so the test is insignificant. There is therefore no evidence that the proportional odds assumption is violated for `contact`.

It is not possible to estimate both  $\beta_2$  and  $\beta_{2j}$  in the same model. Consequently variables that appear in `nominal` cannot enter elsewhere as well. For instance not all parameters are identifiable in the following model:

```
> fm.nom2 <- clm(rating ~ temp + contact, nominal = ~contact, data = wine)
```

We are made aware of this when summarizing or printing the model:

```
> summary(fm.nom2)
```

```

formula: rating ~ temp + contact
nominal: ~contact
data:    wine

link threshold nobs logLik AIC      niter max.grad cond.H
logit flexible  72   -86.21 190.42 6(0)  1.64e-10 4.8e+01

```

Coefficients: (1 not defined because of singularities)

```

      Estimate Std. Error z value Pr(>|z|)
tempwarm      2.519      0.535   4.708  2.5e-06 ***
contactyes      NA         NA      NA      NA
---

```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Threshold coefficients:

```

      Estimate Std. Error z value
1|2.(Intercept) -1.3230    0.5623  -2.353
2|3.(Intercept)  1.2464    0.4748   2.625
3|4.(Intercept)  3.5500    0.6560   5.411
4|5.(Intercept)  4.6602    0.8604   5.416
1|2.contactyes  -1.6151    1.1618  -1.390
2|3.contactyes  -1.5116    0.5906  -2.559
3|4.contactyes  -1.6748    0.6488  -2.581
4|5.contactyes  -1.0506    0.8965  -1.172

```

Scale effects:

Scale effects are usually motivated from the latent variable interpretation of a CLM. Assume the following model for a latent variable:

$$S_i = \alpha + \mathbf{x}_i^T \boldsymbol{\beta}^* + \varepsilon_i, \quad \varepsilon_i \sim N(0, \sigma^{*2}) \quad (4)$$

If the ordinal variable  $Y_i$  is observed such that  $Y_i = j$  is recorded if  $\theta_{j-1}^* < S_i \leq \theta_j^*$ , where

$$-\infty \equiv \theta_0^* < \theta_1^* < \dots < \theta_{J-1}^* < \theta_J^* \equiv \infty \quad (5)$$

then we have the cumulative link model for  $Y_i$ :

$$P(Y_i \leq j) = \Phi(\theta_j - \mathbf{x}_i^T \boldsymbol{\beta})$$

where we have used  $\theta_j = (\theta_j + \alpha)/\sigma$  and  $\boldsymbol{\beta} = \boldsymbol{\beta}^*/\sigma$ , and  $\Phi$  is the inverse probit link and denotes the standard normal CDF. Other assumptions on the distribution of the latent variable,  $S_i$  lead to other link functions.

If the scale (or dispersion) of the latent distribution is described by a log-linear model such that  $\log(\sigma_i) = \mathbf{z}_i^T \boldsymbol{\zeta}$ , then the resulting CLM reads:

$$P(Y_i \leq j) = \Phi\left(\frac{\theta_j - \mathbf{x}_i^T \boldsymbol{\beta}}{\sigma_i}\right) \quad (6)$$

Thus allowing for scale effects corresponds to modelling not only the location of the latent distribution, but also the scale. If the link function is the **probit**, the corresponding latent distribution is Gaussian and the location equals the mean and scale or dispersion equals the spread or standard deviation. Just as the absolute location ( $\alpha$ ) is not identifiable, the absolute scale ( $\sigma$ ) is not identifiable either in the CLM.

We can allow the scale of the latent distribution to depend on temperature in the following way:

$$\text{logit}(P(Y_i \leq j)) = \frac{\theta_j - \beta_1(\text{temp}_i) - \beta_2(\text{contact}_i)}{\exp(\zeta_1(\text{temp}_i))} \quad (7)$$

$$i = 1, \dots, n, \quad j = 1, \dots, J - 1$$

We can estimate this model with

```
> fm.sca <- clm(rating ~ temp + contact, scale = ~temp, data = wine)
> summary(fm.sca)
```

```
formula: rating ~ temp + contact
scale:    ~temp
data:     wine
```

```
link threshold nobs logLik AIC      niter max.grad cond.H
logit flexible  72   -86.44 186.88 8(0)  5.25e-09 1.0e+02
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
tempwarm	2.6294	0.6860	3.833	0.000127	***
contactyes	1.5878	0.5301	2.995	0.002743	**

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

log-scale coefficients:

	Estimate	Std. Error	z value	Pr(> z )
tempwarm	0.09536	0.29414	0.324	0.746

Threshold coefficients:

	Estimate	Std. Error	z value
1 2	-1.3520	0.5223	-2.588
2 3	1.2730	0.4533	2.808
3 4	3.6170	0.7774	4.653
4 5	5.2982	1.2027	4.405

Notice that both location and scale effects of `temp` are identifiable. Also notice that coefficient is given on the log-scale, where the Wald test is more appropriate. The absolute scale of the latent distribution is not estimable, but we can estimate the scale at warm conditions relative to cold conditions. Therefore the estimate of  $\kappa$  in the relation  $\sigma_{warm} = \kappa\sigma_{cold}$  is given by

```
> exp(fm.sca$zeta)
```

```
tempwarm
1.100054
```

However, the scale difference is not significant in this case.

Confidence intervals can be obtained with:

```
> confint(fm.sca, type = "profile")
```

```

                2.5 %    97.5 %
tempwarm      1.4810157 4.2869578
contactyes    0.6274051 2.7360954
sca.tempwarm -0.4912082 0.6775606
```

Observe that the Wald intervals cannot be obtained (at least for the scale parameters) with

```
> confint.default(fm.sca)
```

```

                2.5 %    97.5 %
1|2          -2.3757930 -0.3282906
2|3           0.3844589  2.1615446
3|4           2.0933579  5.1406882
4|5           2.9410702  7.6554023
tempwarm     1.2849407  3.9738962
contactyes   0.5487925  2.6268951
tempwarm     1.2849407  3.9738962
```

but the following will provide them

```
> confint(fm.sca, type = "Wald")
```

```

                2.5 %    97.5 %
1|2          -2.3757930 -0.3282906
2|3           0.3844589  2.1615446
3|4           2.0933579  5.1406882
4|5           2.9410702  7.6554023
tempwarm     1.2849407  3.9738962
contactyes   0.5487925  2.6268951
tempwarm    -0.4811495  0.6718678
```

Model identifiability:

If we attempt to test the proportional odds assumption for `temp`, some peculiarities show up:

```
> fm.nom2 <- clm(rating ~ contact, nominal = ~temp, data = wine)
> summary(fm.nom2)
```

```
formula: rating ~ contact
nominal: ~temp
data:    wine
```



```
link threshold nobs logLik AIC      niter max.grad cond.H
logit flexible 72   -84.90 187.81 16(0) 6.45e-07 2.8e+08
```

Coefficients:

```
      Estimate Std. Error z value Pr(>|z|)
contactyes  1.4652      0.4688   3.125  0.00178 **
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Threshold coefficients:

```
      Estimate Std. Error z value
1|2.(Intercept)  -1.2656      0.5149  -2.458
2|3.(Intercept)   1.1040      0.4388   2.516
3|4.(Intercept)   3.7657      0.8046   4.680
4|5.(Intercept)  19.8964    2145.3568   0.009
1|2.tempwarm    -16.0954    1245.0152  -0.013
2|3.tempwarm     -2.1530      0.5898  -3.650
3|4.tempwarm     -2.8733      0.8174  -3.515
4|5.tempwarm    -17.5500    2145.3569  -0.008
```

Observe that several of the threshold coefficients are extremely large with huge standard errors. Also the condition number of the Hessian is very large. These are all indications that the model is not identifiable. The problem is revealed with

```
> with(wine, table(temp, rating))
```

```
      rating
temp   1  2  3  4  5
cold   5 16 13  2  0
warm   0  6 13 10  7
```

where the zeros indicate the problem. Nevertheless we can still test the proportional odds assumption for temp:

```
> anova(fm1, fm.nom2)
```

Likelihood ratio tests of cumulative link models:

```
      formula:      nominal: link: threshold:
fm1    rating ~ temp + contact ~1      logit flexible
fm.nom2 rating ~ contact      ~temp      logit flexible
```

```
      no.par    AIC  logLik LR.stat df Pr(>Chisq)
fm1          6 184.98 -86.492
fm.nom2       9 187.81 -84.904  3.175  3    0.3654
```

## References

- Randall, J. (1989). The analysis of sensory data by generalised linear model. *Biometrical journal* 7, pp. 781–793.
- Tutz, G. and W. Hennevogl (1996). Random effects in ordinal regression models. *Computational Statistics & Data Analysis* 22, pp. 537–557.