

# Regression Models for Ordinal Data

## Introducing *R*-package **ordinal**

Rune H B Christensen

DTU Informatics, IMM  
Section for Statistics  
Technical University of Denmark  
`rhbc@imm.dtu.dk`

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## Examples of ordinal response variables

- MR scannings of cancer (greatly enlarged, enlarged, no change, smaller, much smaller)
- Smoking frequency (never, occasionally,  $<1$  pack/day,  $>1$  pack/day)
- BMI (underweight, normal weight, overweight, obese)
- Questionnaire (strongly disagree, disagree, undecided, agree, strongly agree)

# Cumulative link models (CLMs)

The cumulative link model — also known as:

- Proportional odds model
- Ordered probit/logit model
- Ordinal regression model

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

# The wine data

**Table:** The wine data (Randall, 1989), N=72

Variables	Type	Values
bitterness	response	1, 2, 3, 4, 5 less — more
temperature	predictor	cold, warm
contact	predictor	no, yes
judges	random	1, . . . , 9

- How does the perceived bitterness of wine depend on temperature and contact?
- A linear model is not a good idea

# The **ordinal** package — an overview

Main functions:

- Cumulative link models (CLMs):  
`clm(formula, data, link, .....)`
- Cumulative link mixed models (CLMMs):  
`clmm(formula, data, link, .....)`  
(lmer syntax)

Other functions:

- `clm.control`
- `clmm.control`
- 15 additional exported function

Numerous methods:

- `summary`, `anova`, `predict`, `confint`, ...

# Existing implementations of cumulative link models

- `polr` from **MASS** — widely used implementation
- `lrm` from **Design**
- `cumulative` from **VGAM**
- `MCMCglmm` from **MCMCglmm** (mixed models)

# Challenges in implementing CLMs

- 1 Intuitive user interface
- 2 Efficient computational methods
- 3 Substantial scope of models
- 4 Useful methods and auxiliary functions
- 5 Readable code
- 6 Comprehensive Documentation

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## Fitting and displaying CLMs with ordinal

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

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

```
link   threshold nobs logLik AIC      niter max.grad cond.H
probit flexible  72   -85.76 183.52 5(0)   1.44e-13 2.2e+01
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )	
tempwarm	1.4994	0.2918	5.139	2.77e-07	***
contactyes	0.8677	0.2669	3.251	0.00115	**

---

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

Threshold coefficients:

	Estimate	Std. Error	z value
1 2	-0.7733	0.2829	-2.734
2 3	0.7360	0.2499	2.945
3 4	2.0447	0.3218	6.353

# Aliased coefficients

```
> fm.soup <- clm(SURENESS ~ PRODID * DAY, data = soup)
```

```
> summary(fm.soup)
```

```
formula: SURENESS ~ PRODID * DAY
```

```
data:      soup
```

```
link threshold nobs logLik   AIC      niter max.grad cond.H
logit flexible  1847 -2672.08 5374.16 6(1)  1.95e-13 9.4e+02
```

```
Coefficients: (1 not defined because of singularities)
```

```
Estimate Std. Error z value Pr(>|z|)
```

PRODID2	0.6665	0.2146	3.106	0.00189	**
PRODID3	1.2418	0.1784	6.959	3.42e-12	***
PRODID4	0.6678	0.2197	3.040	0.00237	**
PRODID5	1.1194	0.2400	4.663	3.11e-06	***
PRODID6	1.3503	0.2337	5.779	7.53e-09	***
DAY2	-0.4134	0.1298	-3.186	0.00144	**
PRODID2:DAY2	0.4390	0.2590	1.695	0.09006	.
PRODID3:DAY2	NA	NA	NA	NA	
PRODID4:DAY2	0.3308	0.3056	1.083	0.27892	
PRODID5:DAY2	0.3871	0.3248	1.192	0.23329	

## Likelihood ratio tests of CLMs

```
> fm2 <- update(fm1, ~. - temp)
> anova(fm1, fm2)
```

Likelihood ratio tests of cumulative link models:

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

```
      no.par   AIC   logLik LR.stat df Pr(>Chisq)
fm2      5 210.05 -100.026
fm1      6 183.52 -85.761  28.529  1 9.231e-08 ***
```

```
---
```

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

# Computational challenges

- Robust starting values
  - The `c1m` should always converge from the default starting value
  - It should be possible to supply starting values
- Speedy model estimation
  - Speed is maintained despite model scope and flexibility
- Accurate estimates
- Accurate standard errors

# Accuracy of parameter estimates

```
> fm1
formula: rating ~ temp + contact
data:    wine

link    threshold nobs logLik AIC    niter max.grad
probit flexible  72   -85.76 183.52 5(0)  1.44e-13
```

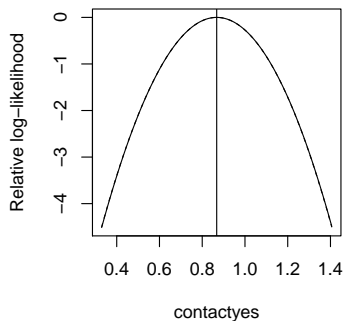
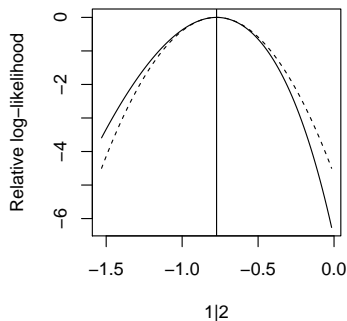
```
Coefficients:
  tempwarm contactyes
    1.4994      0.8677
```

```
Threshold coefficients:
  1|2    2|3    3|4    4|5
-0.7733 0.7360 2.0447 2.9413
```

- Has the model converged?
- How accurate are these estimates?

# Assessment of model convergence

```
> slice.fm1 <- slice(fm1, parm = c(1, 6))
> par(mfrow = c(1, 2))
> plot(slice.fm1)
```



# Assessment of parameter accuracy

```
> convergence(fm1)
```

```
nobs logLik niter max.grad cond.H logLik.Error
72 -85.76 5(0) 1.44e-13 2.2e+01 0.00e+00
```

	Estimate	Std.Err	Gradient	Error	Cor.Dec	Sig.Dig
1 2	-0.7733	0.2829	1.59e-14	1.91e-16	15	15
2 3	0.7360	0.2499	1.31e-13	-5.65e-16	14	14
3 4	2.0447	0.3218	-1.44e-13	-8.26e-15	13	14
4 5	2.9413	0.3873	-6.46e-15	-7.72e-15	13	14
tempwarm	1.4994	0.2918	-1.38e-14	-5.00e-15	14	15
contactyes	0.8677	0.2669	1.88e-15	-2.25e-15	14	14

```
Eigen values of Hessian:
```

```
61.616 53.876 32.283 17.241 13.393 2.825
```

## Extending the model class

- Scale effects

```
clm(rating ~ contact, scale =~ temp, data=wine)
```

- Structured thresholds

```
clm(rating ~ contact, data=wine, threshold="symmetric")  
clm(rating ~ contact, data=wine, threshold="equidistant")
```

- Nominal effects (partial proportional odds)

```
clm(rating ~ contact, nominal =~ temp, data=wine)
```

- Flexible link functions

- Random effects

- For grouped and multilevel data



# Cumulative link mixed models (CLMMs)

- Multiple random effect terms
  - Nested and crossed random effect structures
  - No correlated random effects (yet)
  - No random slopes (yet)
- Computational methods
  - Laplace approximation
  - Adaptive Gauss-Hermite quadrature (+ non-adaptive GHQ)

Example:

```
> fm.ran <- clmm(rating ~ contact + temp + (1 | judge), data = wine)
```

## Methods for `clm` fits

- Standard methods:  
`print`, `summary`, `anova`, `predict`
- Extractor methods:  
`coef`, `vcov`, `logLik`, `AIC`, `fitted`, ...
- Model development and selection:  
`drop1`, `add1`, `step`
- Model assessment methods:  
`profile`, `plot.profile`, `confint`
- Numerous additional methods

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- Standard methods:  
`print`, `summary`, `anova`, `predict with se and CI`
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# Summary

- Reliable computational methods
- Methods for assessing convergence
- Extends the basic model with:
  - scale effects
  - nominal effects
  - random effects
  - structured thresholds
- A suite of helpful methods for `c1m` and `c1mm` objects

## Future work

- slice and convergence methods for `clmm` fits
- More flexible random effect structures
- AGQ methods for nested random effects

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# Bibliography

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