

# Handling Ordinal Predictors in Regression Models via Monotonic Effects

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# Linear Regression

Assume that the predictor term  $\eta$  is a linear combination of the predictor variables multiplied by the regression coefficients:

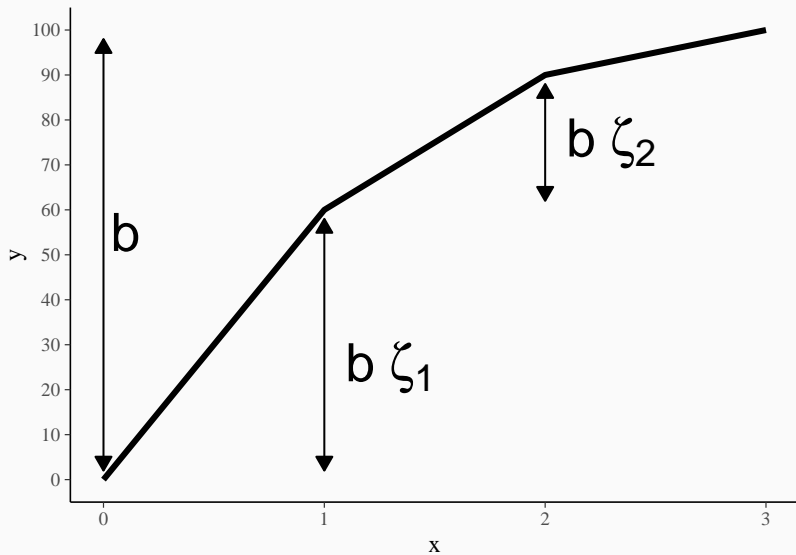
$$\eta = b_0 + \sum_{k=1}^K b_k x_k$$

Predictors  $x_k$  may be

- continuous variables
- coded categorical variables

**What about ordinal predictors?**

## Monotonic Effects: Idea



# Monotonic Effects: Mathematical Formulation

Monotonic regression of an ordinal predictor  $x \in \{0, \dots, C\}$ :

$$\eta = b_0 + b \sum_{i=1}^x \zeta_i$$

- For notational convenience:  $\sum_{i=1}^0 \zeta_i = 0$
- Parameter  $\zeta$  is a simplex:  $\zeta_i \in [0, 1]$  and  $\sum_{i=1}^C \zeta_i = 1$
- Parameter  $b$  may be any real value

Implications:

- Effect of  $x$  is either monotonically increasing or decreasing
- $b$  indicates the direction and scale of the effect
- Categories are equidistant if and only if  $\zeta_i = 1/C$

## Monotonic Effects: Interactions

Ordinary Regression model including the interaction of  $z$  and  $x$ :

$$\eta = b_0 + b_1 z + b_2 x + b_3 z x$$

Generalization to monotonic effects:

- Define  $\text{mo}(x, \zeta) := \sum_{i=1}^x \zeta_i$  for brevity
- Replace  $x$  with  $\text{mo}(x, \zeta)$ :

$$\eta = b_0 + b_1 z + b_2 \text{mo}(x, \zeta_{b_2}) + b_3 z \text{mo}(x, \zeta_{b_3})$$

- Relation of  $\zeta_{b_2}$  and  $\zeta_{b_3}$  determines the type of monotonicity
- $x$  is (conditionally) monotonic for all  $z$  if  $\zeta_{b_2} = \zeta_{b_3}$

# Monotonic Effects in a Bayesian Framework

Priors on  $b$ :

- Any reasonable prior for regression coefficients
- For instance:  $b \sim \mathcal{N}(0, s)$  for a fixed standard deviation  $s$

Prior on  $\zeta$ :

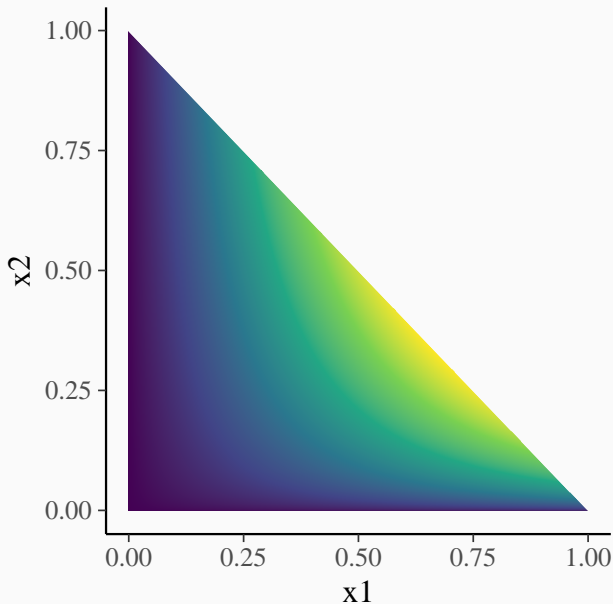
- Dirichlet prior:  $\zeta \sim \mathcal{D}(\alpha)$
- $\alpha$ : Concentration parameter of the same length as  $\zeta$

Let  $\alpha_0 = \sum_{i=1}^C \alpha_i$ , then:

$$\mathbb{E}(\zeta_i) = \frac{\alpha_i}{\alpha_0}$$

$$\text{SD}(\zeta_i) = \sqrt{\frac{\alpha_i(\alpha_0 - \alpha_i)}{(\alpha_0^2(\alpha_0 + 1))}}$$

## Dirichlet Prior: Visualization for $\alpha = (2, 1.5, 1)$



# Monotonic effects in the R package brms

**brms** is a comprehensive framework for Bayesian regression models

**Stan** is used for the model fitting behind the scenes

Monotonic effects are fully built into the formula syntax of brms

Monotonic effect of  $x$  on  $y$ :

```
y ~ mo(x)
```

Main effects and interaction of  $x$  and  $z$ :

```
y ~ mo(x) * z
```

Varying effect of  $x$  over group  $g$ :

```
y ~ mo(x) + (mo(x) | g)
```



## Case Study: Measures of Chronic Widespread Pain (CWP)

Objective: Predict subjective physical health by measures of CWP

Examples for CWP measures:

- Impairments in walking
- Impairments in moving around

Scale from 0 ('no problem') to 4 ('complete problem')

Data provided in the **ordPens** package

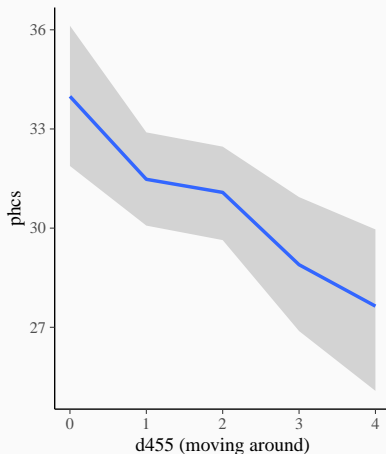
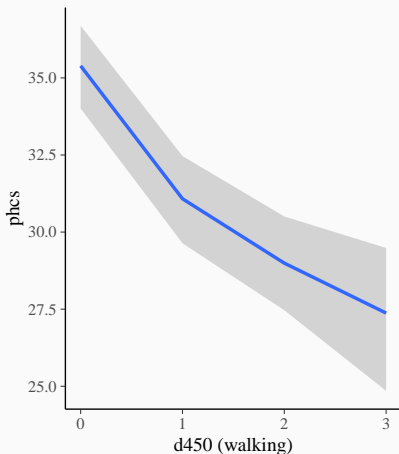
For details see Gertheiss, Hogger, Oberhauser, & Tutz (2011)

Plausible assumption: CWP measures have **monotonic effects**

# Case Study: Model Specification

```
library(brms)
```

```
fit1 <- brm(phcs ~ mo(d450) + mo(d455), data = cwp)
```



## Other Approaches for Modelling Ordinal Predictors

Categorical isotonic regression:

- Estimate group means of ordinal categories such that  $\mu_0 < \mu_1 < \dots < \mu_C$
- Equivalent to monotonic effects in simple cases
- Harder to penalize via priors

Penalized regression (Gertheiss & Tutz, 2009):

- Apply dummy coding on the ordinal variable
- Penalize larger differences between adjacent categories via

$$J(b) = \sum_{i=1}^C (b_i - b_{i-1})^2$$

- Closely related to regression splines
- No monotonicity constraint

## Learn More about Monotonic Effects and brms

Manuscript draft:

<https://github.com/paul-buerkner/monotonic-effects-paper>

Vignette in brms: `vignette("brms_monotonic")`

Documentation of the formula syntax: `?brmsformula`

Papers about brms: Bürkner (2017) and Bürkner (2018)

Forums: <http://discourse.mc-stan.org/>

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## References

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, 80(1), 1–28.

<https://doi.org/10.18637/jss.v080.i01>

Bürkner, P.-C. (2018). Advanced Bayesian multilevel modeling with the R package brms. *The R Journal*, 1–15.

Gertheiss, J., Hogger, S., Oberhauser, C., & Tutz, G. (2011). Selection of ordinally scaled independent variables with applications to international classification of functioning core sets. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 60(3), 377–395.

Gertheiss, J., & Tutz, G. (2009). Penalized regression with ordinal predictors. *International Statistical Review*, 77(3), 345–365.

# Appendix

# Counter Example to the Conditional Monotonicity

Model:  $\eta = b_0 + b_1 z + b_2 \text{mo}(x, \zeta_{b_2}) + b_3 z \text{mo}(x, \zeta_{b_3})$

