

## rcrologit

The package provides estimation and inferential procedures for rank-ordered logit model with agents with heterogeneous taste preferences.

### Setup

We have  $n$  i.i.d. random draws

$$\mathcal{D} := (Y_i, X_i)_{i=1}^n$$

where  $Y_i := (Y_{i0}, Y_{i1}, \dots, Y_{iJ})^\top$ ,  $Y_{i\ell} = 0, 1, \dots, J$ , is a vector of ranks and  $C_i := (X_{i0}, C_{i1}, \dots, C_{iJ})^\top \in \mathbb{R}^{(J+1) \cdot K}$ ,  $C_{i\ell} \in \mathbb{R}^K$ . Let the latent utility model (McFadden, 1974) be

$$U_{ij}^* = u_{ij} + \epsilon_{ij}, \quad \epsilon_{ij} \stackrel{\text{iid}}{\sim} \text{Gu}(0, 1).$$

For notational convenience, define the functions  $r_i : \{0, 1, \dots, J\} \rightarrow \{0, 1, \dots, J\}$ ,  $i = 1, \dots, n$ . Such functions map the rank  $j \in \{0, 1, \dots, J\}$  into the corresponding item  $r(j) \in \{0, 1, \dots, J\}$  according to individual  $i$ 's preferences. To clarify

$$Y_{ij} = k \quad \Longleftrightarrow \quad r_i(k) = j$$

An observed ranking for a respondent implies a complete ordering of the underlying utilities. An individual will prefer an item with a higher utility over an item with a lower utility. If we observe a full ranking  $r_i := (r_i(0), r_i(1), \dots, r_i(J))^\top$ , we know that

$$U_{ir_i(0)}^* > U_{ir_i(1)}^* > \dots > U_{ir_i(J)}^*.$$

Therefore, the probability of observing a particular ranking  $r_i$  is given by

$$\mathbb{P}[r_i \mid \mathcal{D}] = \mathbb{P}\left[U_{ir_i(0)}^* > U_{ir_i(1)}^* > \dots > U_{ir_i(J)}^* \mid \mathcal{D}\right] = \prod_{j=0}^{J-1} \frac{\exp(u_{ir_i(j)})}{\sum_{j \leq \ell \leq J} \exp(u_{ir_i(\ell)})}.$$

In light of this, we can see that the rank-ordered logit is nothing else than a series of multinomial logit (MNL) models: when  $j = 0$  we considered a MNL the most preferred item; another MNL for the second-ranked item to be preferred over all items except the one with rank 1, and so on. Finally, the probability of a complete ranking is made up of the product of these separate MNL probabilities. The product contains only  $J$  probabilities, because ranking the least preferred item is done with probability 1.

### Modelling

In its most general form, we allow the user to model  $u_{i\ell}$  in the latent utility model as

$$u_{i\ell} = X_{i\ell}^\top \beta_F + Z_i^\top \alpha_{\ell, F} + W_{i\ell}^\top \beta_i + V_i^\top \alpha_{i\ell} + \delta_\ell$$

An alternative, handier way to rewrite the model above is to define  $Z_{i\ell} := \sum_{j=1}^J Z_i \times \mathbf{1}(j = \ell)$  and  $V_{i\ell} :=$

$\sum_{j=1}^J V_i \times \mathbf{1}(j = \ell)$ ,  $\ell = 1, 2, \dots, J$ , and consider the equivalent model

$$u_{i\ell} = X_{i\ell}^\top \beta_F + Z_{i\ell}^\top \alpha_F + W_{i\ell}^\top \beta_i + V_{i\ell}^\top \alpha_i + \delta_\ell,$$

where:

- $X_{i\ell}$  are covariates varying at the unit-alternative level whose coefficients are modelled as fixed
- $Z_i$  are covariates varying at the unit level whose coefficients are modelled as fixed
- $W_{i\ell}$  are covariates varying at the unit-alternative level whose coefficients are modelled as random
- $V_i$  are covariates varying at the unit level whose coefficients are modelled as random the random coefficients
- The heterogeneous taste coefficients are modeled as a joint multivariate normal and are i.i.d. across units with mean  $\left[\alpha_R^\top, \beta_R^\top\right]^\top$  and variance  $\Sigma$ .
- $\delta_\ell$  are alternative-specific fixed effects
- $\epsilon_{i\ell} \sim \text{Gu}(0, 1)$  are idiosyncratic i.i.d. shocks

Note that whenever  $W_{i\ell}$  and  $V_i$  are not specified estimates a standard rank-ordered logit with no heterogeneous preferences and the conditional choice probabilities are given by

$$\mathbb{P}[r_i | \mathcal{D}] = \prod_{j=0}^{J-1} \frac{\exp(u_{ir_i(j)})}{\sum_{j \leq \ell \leq J} \exp(u_{ir_i(\ell)})}.$$

If instead agents are allowed to have heterogeneous taste, then

$$\mathbb{P}[r_i | \mathcal{D}] = \int \prod_{j=0}^{J-1} \frac{\exp(u_{ir_i(j)}^\top(\beta_i))}{\sum_{j \leq \ell \leq J} \exp(u_{ir_i(\ell)}^\top(\beta_i))} \phi(\beta_i; \beta, \Sigma) d\beta_i.$$

The parameter vector to be estimated is thus

$$\theta = \left( \beta_F^\top, \beta_R^\top, \alpha_F^\top, \alpha_R^\top, \text{vech}(\Sigma)^\top, \{\delta\}_{j=1}^J \right)^\top.$$

## Estimation

The ideal maximum likelihood estimator is defined as

$$\hat{\theta}_{\text{ML}} := \arg \max_{\theta} \sum_{i=1}^n \log \int \prod_{j=0}^{J-1} \frac{\exp(u_{ir_i(j)}(\theta))}{\sum_{j \leq \ell \leq J} \exp(u_{ir_i(\ell)}(\theta))} \phi(\beta_i; \beta_R, \Sigma) d\beta_i.$$

We approximate the integral via montecarlo as

$$\hat{\mathbb{P}}_{(\hat{\beta}, \hat{\Sigma})}[r_i | \mathcal{D}] = \frac{1}{S} \sum_{i=1}^S \prod_{j=0}^{J-1} \frac{\exp(u_{ir_i(j)}(\theta, \beta_i^{(s)}))}{\sum_{j \leq \ell \leq J} \exp(u_{ir_i(\ell)}(\theta, \beta_i^{(s)}))},$$

where  $\beta_i \stackrel{\text{iid}}{\sim} \text{N}(\hat{\beta}_R, \hat{\Sigma})$ .

## Installation

You can install the development version of rcrologit from GitHub with:

```
# install.packages("devtools")
devtools::install_github("filippopalomba/rcrologit")
```

## Basic Usage

```
library(rcrologit)

data <- rcrologit_data

# Rank-ordered logit
dataprep <- dataPrep(data, idVar = "Worker_ID", rankVar = "rank",
                    altVar = "alternative",
                    covsInt.fix = list("Gender"),
                    covs.fix = list("log_Wage"), FE = c("Firm_ID"))

rologitEst <- rcrologit(dataprep)

# Rank-ordered logit
dataprep <- dataPrep(data, idVar = "Worker_ID", rankVar = "rank",
                    altVar = "alternative",
                    covsInt.het = list("Gender"),
                    covs.fix = list("log_Wage"), FE = c("Firm_ID"))

rologitEst <- rcrologit(dataprep, stdErr="skip")
```