ol-lv

```r
library(DCM)
N <- 10e3
```

Simulate data

We first simulate ordered-logit data with one latent variable.

```r
# Simulate LV
X <- data.frame(x1 = rnorm(N), x2 = rnorm(N))
betas_lv <- c(beta1 = 1, beta2 = 2)
taus_lv <- c(tau1 = -1, tau2 = 1)
zetas <- c(zeta1 = 1, zeta2 = 2)

sim_dat_lv <- DCM::simulate_lv(X, betas_lv, taus_lv, zetas, N)
lv <- sim_dat_lv$lv
obs_lv <- sim_dat_lv$obs

# Pass and simulate OL data
X <- data.frame(x1 = rnorm(N), x2 = lv)
betas <- c(beta1 = 1, beta2 = 2)
taus <- c(tau1 = -1, tau2 = 1) # will generate 3 choices
sim_dat_ol <- simulate_ol(X, betas, taus, N)
obs_ol <- sim_dat_ol[, names(sim_dat_ol) != "x2"] # x2 is our lv

# What we actually observe
X <- data.frame(
  obs_lv,
  obs_ol
)

names(X) <- c("x1_lv", "x2_lv", "ind1", "ind2", "x1_ol", "choice")
head(X)
#>        x1_lv      x2_lv ind1 ind2      x1_ol choice
#> 1  0.3808537 -1.1335948    2    1  0.3452868      1
#> 2  1.6683449 -0.2505395    3    3  0.2198743      3
#> 3  0.5567137  0.1520942    1    1 -1.6975887      1
#> 4 -0.3621972  0.9733798    1    1  0.2377974      2
#> 5 -0.9779265  1.0056771    3    3  0.7001523      3
#> 6  0.9269835 -0.5215959    1    1  1.5317879      2
```

So the assumed behavioural process reads:

$$P(y = k|x)^{ol} = f(U_{ol}) = f(\beta_0 + \beta_1 LV + \beta_2 x1_{ol}) \tag{1}$$

Further the latent variable can be grasped by observing individuals ($x1_{lv}, x2_{lv}$) choosing indicators ($ind1, ind2$). Therefore the probability ob observing individual n choosing the indicator tuple ($ind1, ind2$) follows an ordered logit model (measurement equation, taken the latent variable as given). The structural equation reads:

$$LV = \beta_{1lv} x_{1lv} + \beta_{2lv} x_{2lv} + \psi \tag{2}$$

where psi is assumed to be normally distributed.