…The data will include a treatment or exposure indicator and an ordinal categorical outcome with four possible responses. In this case, the log odds-ratio comparing the odds for the treatment group with the control group will be -1.3, which translates to an odds ratio (OR) of 0.27.

```
d1 <- defDataAdd(varname = "z", formula = "rx * 1.3", dist =
"nonrandom")

set.seed(382763)
dd <- genData(100000)
dd <- trtAssign(dd, grpName = "rx")
dd <- addColumns(d1, dd)

baseprobs <- c(.4, .3, .2, .1)
dd_p <- genOrdCat(dtName = dd, adjVar = "z", baseprobs = baseprobs)
```

Here is a calculation of the cumulative proportions and odds, as well as the odds ratios, which are all close to -1.3:

```
(prop <- prop.table(dd_p[, table(rx, cat)], 1))
##    cat
## rx     1    2    3    4
##    0 0.40 0.30 0.20 0.10
##    1 0.15 0.24 0.32 0.29
(cumprop <- data.table(apply(prop, 1, cumsum)))
##      0    1
## 1: 0.4 0.15
## 2: 0.7 0.39
## 3: 0.9 0.71
## 4: 1.0 1.00
(cumodds <- cumprop[, .(odds0 = `0`/(1 - `0`), odds1=`1`/(1 - `1`))])
##    odds0 odds1
## 1:  0.67  0.18
## 2:  2.32  0.63
## 3:  8.84  2.45
## 4:   Inf   Inf
cumodds[1:3, odds1/odds0]
## [1] 0.27 0.27 0.28
```

To visualize cumulative proportional odds, here's a plot using the really nice `likert` package:

```
library(likert)

item <- data.frame(dd_p[, "cat"])
names(item) <- "response"
bin.grp <- factor(dd_p[, rx])
likert.bin <- likert(item, grouping = bin.grp)

plot(likert.bin) + ggtitle("Proportional odds")
```
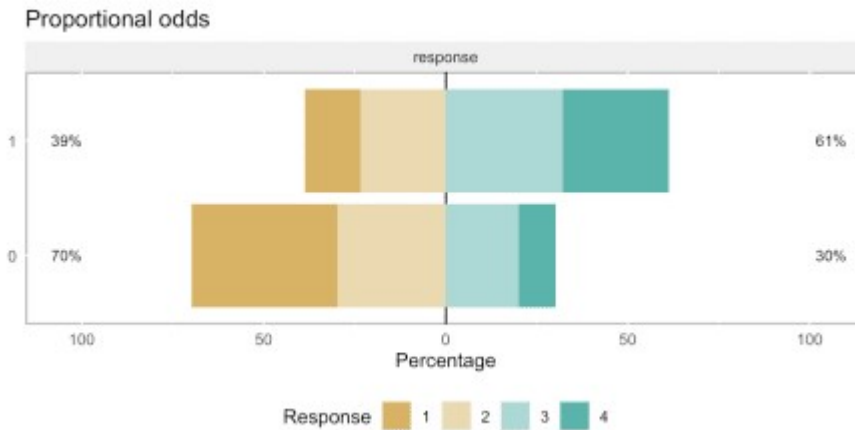
Proportional odds

It's now simple to relax the proportionality assumption

Two arguments are needed to relax the assumption: `npVar` and `npAdj`. The user specifies the first argument to indicate what variable is driving the lack of proportionality. In this case, it will be the treatment itself, since that is the only covariate in the data set. The second argument is a vector that represents the violation of the assumption at each level of the ordinal measure. The length of this vector is currently the same length as the number of ordinal categories, though the last value will always be 0.

In this example, the cumulative log-odds ratio for the first category will be 0.3 points more than the proportional assumption of -1.3, so should be quite close to -1.0 (or 0.37 on the OR scale). The cumulative log-odds ratio (and OR) for the second category will be the same as in the case of proportionality. And, the cumulative log-odds ratio for the third category will be 1.0 less than -1.3, or around -2.3 (which translates to 0.10 on the OR scale)

```
npAdj <- c(-0.3, 0.0, 1.0, 0)
dd_np <- genOrdCatNP(dtName = dd, adjVar = "z", baseprobs = baseprobs,
                npVar = "rx", npAdj = npAdj)

cumprop <- data.table(apply(prop.table(dd_np[, table(rx, cat)], 1), 1,
cumsum))
cumodds <- cumprop[, .(odds0 = `0`/(1 - `0`), odds1=`1`/(1 - `1`))]
cumodds[1:3, odds1/odds0]
## [1] 0.37 0.27 0.10
```

And here is what non-proportional cumulative odds looks like:

Non-proportional odds