Multinomial and ordered logits

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GLM: A recap

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$\Rightarrow$ *Probability distribution maps unobserved variable to observed outcomes.*

Ordered logistic regression

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$\Rightarrow$ *estimate a single set of regression parameters, but keep the information on the order without assuming a continuous variable.*

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Latent variable approach: cutpoints

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- **Ordinal logistic:** Serveral cutpoints. $\rightarrow$ Explicit.

$\Rightarrow$ *Model estimates both regression parameters (β) and cutpoints (τ).*

A series of cutpoints

You are in the category m when the latent variable is between its two cutpoints: $\tau_{m-1} < y^\star < \tau_m$

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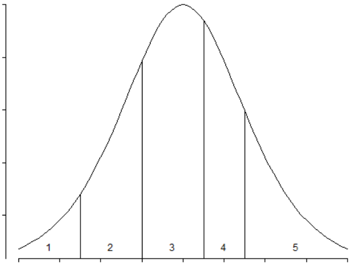

Figure 1: Slicing up a latent variable

The regression coefficients

The model calculates the odds of being lower than τ_m

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- The first cutpoint (τ_0) is 0 ($-inf$): you cant be lower than the lowest.
- The last cutpoint is 1 ($+inf$): all observations are in some category.
- You end up with $m-1$ cutpoints.

The regression output

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The predicted value

The predicted probability of being in category m:

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$$Pr(y_i = m) = \frac{exp(\tau_m - \beta x_i)}{1 + exp(\tau_m - \beta x_i)} - \frac{exp(\tau_{m-1} - \beta x_i)}{1 + exp(\tau_{m-1} - \beta x_i)} \tag{1}$$

An example: Attitudes towards redistribution

An example:

ESS respondents (that voted V or DF) are asked to what extent they believe the state should engage in redistribution (1 = disagree; 5 = agree).

```
#Load in data
df <- read.table(
  "https://siljehermansen.github.io/teaching/beyond-linear-models/kap10.txt

#Check distribution
barplot(table(df$Udjaevn))
```

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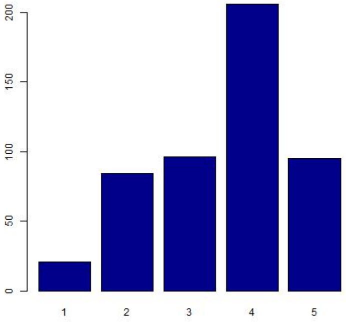

Figure 2: Attitudes towards redistribution is an ordered variable

Attitudes towards redistribution as a function of income

```r
#Library for ordinal regression
library(MASS)
#Recode into ordered factor
df$Udjaevn.ord <- as.ordered(as.factor(df$Udjaevn))
#Run regression
mod.ord <- polr(Udjaevn.ord ~ Indtaegt,
                df,
                method = "logistic",
                Hess = TRUE)
summary(mod.ord)
```

Attitudes towards redistribution as a function of income

```
## Call:
## polr(formula = Udjaevn.ord ~ Indtaegt, data = df, Hess = TRUE,
##     method = "logistic")
##
## Coefficients:
##           Value Std. Error t value
## Indtaegt 0.1153    0.03155   3.653
##
## Intercepts:
##     Value   Std. Error t value
## 1|2 -2.4186  0.2903    -8.3306
## 2|3 -0.6008  0.2179    -2.7566
## 3|4  0.3069  0.2150     1.4277
## 4|5  2.2276  0.2403     9.2686
##
## Residual Deviance: 1298.396
## AIC: 1308.396
## (51 observations deleted due to missingness)
```

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- Effect in logodds: `0.115`
- We can backtransform to one unit increase in x: $(exp(\beta) - 1) \times 100$ $= 12\%$ increase in likelihood of a higher category.

$\Rightarrow$ *Hypothesis testing as in a binomial logit*

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$\Rightarrow$ *The model does a fair job in distinguishing between categories.*

Predicted scenarios

We interpret predicted probability by choosing one level of x and one category (two cutpoints) of y: What is the probability of m?

$$Pr(y_i = m) = \frac{exp(\tau_m - \beta x_i)}{1 + exp(\tau_m - \beta x_i)} - \frac{exp(\tau_{m-1} - \beta x_i)}{1 + exp(\tau_{m-1} - \beta x_i)} \qquad (2)$$

Example

Let's choose low-income respondents (x = 1) and category 3 (diff between cutpoints 2 and 3)

```
z = mod.ord$zeta
x = 1

logodds1 <- z[3] - coefficients(mod.ord) * x
logodds2 <- z[3-1] - coefficients(mod.ord) * x
## Probabilities
p1 <- exp(logodds1)/(1 + exp(logodds1)) #3|4 or lower
p2 <- exp(logodds2)/(1 + exp(logodds2)) #2|3 or lower
## Difference between cutpoints
p1 - p2 #cat 3
```

An example

Predicted proportion in category

```
paste(round((p1-p2)*100),
"% of low-income respondents are predicted to answer x = 3 ('neutral')." )
```

[1] "22 % of low-income respondents are predicted to answer x = 3 ('neutral')."

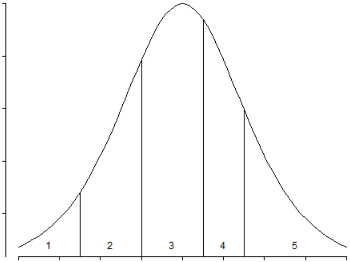
Cumulative probability

```
paste(round((p1)*100),
"% of low-income respondents are predicted to answer x = 3 ('neutral') or l
```

[1] "55 % of low-income respondents are predicted to answer x = 3 ('neutral') or lower to the question of whether they support redistribution."

Two ways of viewing the slicing

We can report the probability (e.g. `0.22`) of ending up between two cutpoints, or the *cumulative* probability (e.g. `0.55`) to be below each



point.

Exercice:

Increase the τ (z) within each value of Income (x)

```
##Create empty plot
plot(y = 0,
     x = 0,
     axes = FALSE,
     xlim = c(1,4),
     ylim = c(0,1),
     ylab = "Probability of z or below",
     xlab = "Thresholds",
     main = "Cumulative probability \nof support for redistribution",
     type = "n")
axis(1, at = 1:length(p1),
     labels = names(p1))
axis(2)
```

Exercice:

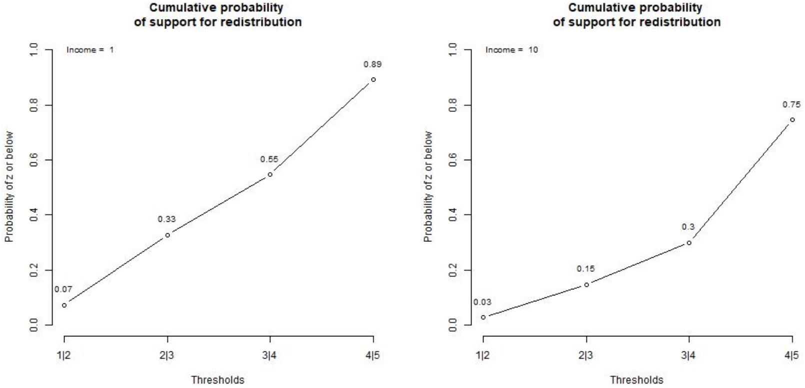
Increase the τ (z) within each value of Income (x)

```
#Set values for prediction
x = 10 #Let this go from 1 to 10; check the shape of 10
z = mod.ord$zeta
#Logodds
logodds1 <- z - coefficients(mod.ord) * x
#Probabilities
p1 <- exp(logodds1)/(1 + exp(logodds1)) #3/4 or lower

#Plot probabilities
lines(y = p1,
      x = 1:length(p1),
      type = "b")
#Set legend (report x-value)
legend("topleft",
       bty = "n",
       cex = 0.8,
     paste("Income = ", x))

#Plot probabilities
text(y = p1+0.06,
```

Result


Cumulative probability
of support for redistribution
Income = 1
Probability of z or below
Thresholds
1|2
2|3
3|4
4|5
0.0
0.2
0.4
0.6
0.8
1.0
0.07
0.33
0.55
0.89
Cumulative probability
of support for redistribution
Income = 10
Probability of z or below
Thresholds
1|2
2|3
3|4
4|5
0.0
0.2
0.4
0.6
0.8
1.0
0.03
0.15
0.3
0.75

Parallel regressions approach: for assessment

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- The y is recoded into $m-1$ dummy variables indicating if $y \leq m$
- Run a series of regressions where all β are fixed (i.e.: the same).

$\Rightarrow$ *This is also useful when we assess the model*

How good is our model?

The basic assumption

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```
df %>%
  filter(!is.na(Udjaevn)) %>%
  group_by(Udjaevn) %>%
  summarize(mean(Indtaegt, na.rm = T))
```

```
## # A tibble: 5 x 2
##   Udjaevn `mean(Indtaegt, na.rm = T)`
##     <dbl>                       <dbl>
## 1       1                        4.8
## 2       2                        5.58
## 3       3                        5.96
## 4       4                        6.41
## 5       5                        6.75
```

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## 3       3                        5.96
## 4       4                        6.41
## 5       5                        6.75
```

- Run parallel regressions without contstraint on β. Are they similar?

An example of parallel regressions

Recode into dummies

The dummies flag cases below a cumulative threshold of *outcomes*

```
##
df$ut1 <- ifelse(df$Udjaevn > 1, 1 , 0) #2 or above
df$ut2 <- ifelse(df$Udjaevn > 2, 1 , 0) #3 or above
df$ut3 <- ifelse(df$Udjaevn > 3, 1 , 0) #4 or above
df$ut4 <- ifelse(df$Udjaevn > 4, 1 , 0) #5
```

$\Rightarrow$ *The model then runs 4 regressions where β reports an aggregated value from all 4 coefficients (think: weigted mean).*

Run four regressions

Let's examplify with the parallel regressions without fixed β:

```
##Parallel regressions:
mod1 <- glm(ut1 ~ Indtaegt, df, family = "binomial")
mod2 <- glm(ut2 ~ Indtaegt, df, family = "binomial")
mod3 <- glm(ut3 ~ Indtaegt, df, family = "binomial")
mod4 <- glm(ut4 ~ Indtaegt, df, family = "binomial")
```

Compare coefficients from four regressions

```
##
## ===========================================================
##                            Dependent variable:
##                    ----------------------------------------
##                      ut1       ut2       ut3        ut4
##                      (1)       (2)       (3)        (4)
## -----------------------------------------------------------
## Indtaegt          0.189**  0.125*** 0.110***  0.094**
##                   (0.085)  (0.041)  (0.035)   (0.045)
##
## Constant          2.048*** 0.552**   -0.270  -2.082***
##                   (0.474)  (0.260)  (0.231)   (0.319)
##
## -----------------------------------------------------------
## Observations        459      459      459       459
## Log Likelihood    -79.653  -234.669 -303.983 -217.674
## Akaike Inf. Crit. 163.306  473.338  611.967   439.348
## ===========================================================
## Note:                        *p<0.1; **p<0.05; ***p<0.01
```

Coefficient should be a weighted average from four regressions

These βs are weighted by the number of observations in each category:

```
table(df$Udjaevn)
```

```
##
##   1   2   3   4   5
##  21  84  96 206  95
```

We can plot the βs for comparison:

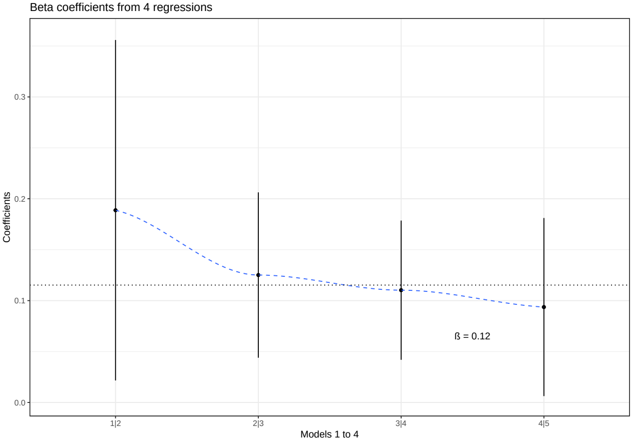
```
results <- rbind(summary(mod1)$coefficients[2, c(1,2)],
                 summary(mod2)$coefficients[2, c(1,2)],
                 summary(mod3)$coefficients[2, c(1,2)],
                 summary(mod4)$coefficients[2, c(1,2)])
thresholds <- c("1|2","2|3","3|4","4|5")
```

We can plot the βs for comparison:

```
ggplot() +
  geom_point(aes(y = results[, "Estimate"],
                 x = thresholds)) +
  geom_smooth(aes(y = results[, "Estimate"],
                  x = 1:4),
              lty = 2,
              lwd = 0.5) +
  geom_segment(aes(x = 1:4,
               xend = 1:4,
               y = results[, "Estimate"]-results[, "Std. Error"]*1.96,
               yend = results[, "Estimate"]+results[, "Std. Error"]*1.96)) +
  theme_bw() +
  ylim(c(results[, "Estimate"][4]-results[, "Std. Error"][4]*2,
         results[, "Estimate"][1]+results[, "Std. Error"][1]*2)) +
  geom_hline(yintercept = mod.ord$coefficients,
             lty = 3) +
  geom_text(aes(y = mod.ord$coefficients-0.05,
                x = 3.5,
                label = paste("\u03b2 =", round(mod.ord$coefficients,2))
                ),
            parse = F) +
  labs(title = "Beta coefficients from 4 regressions") +
  ylab("Coefficients") +
  xlab("Models 1 to 4")
```

We can plot the βs for comparison:

The overall β is `0.12`. If the ordered model describes the data well, then all the unconstrained βs should ressemble that description.



A visual inspection

A more visual way of checking the "parallel lines assumption" is to inspect if the regression lines are parallel.

When is it smart to run an ordered logit?

- You have few ordered categories

When is it smart to run an ordered logit?

- You have few ordered categories
- The effect is approximately the same across the categories (parallel lines assumption)

What do I do if the assumption doesn't hold?

- Run an OLS/linear model:
    - if you have many categories
    - fairly equal spread of observations between categories

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- Run an OLS/linear model:
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- Run a multinomial model:
  - i.e. estimate different β for each regression/threshold

Discrete choice models

Dependent variable: nominal

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  - Multinomial: Models *chooser* characteristics
  - Conditional logit: Models *choice* characteristics

Multinomial logistic regression

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- **A series of binomial logits** with the same reference category.
- **Latent variable approach:** Our utility of each choice.

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- Data is subset to compare two groups $\rightarrow$ data/variation intensive model choice.
- Categories/choice are mutually exclusive $\rightarrow$ Different β for each subset/choice

$\Rightarrow$ *All choices are given a probability and they sum up to one.*

Two conceptions of multinomial regression

Latent variable approach: Imagine k choices modeled as $y_m = \alpha_m \times \beta_m x$

- $\beta_m x_i$ reflects the utility of a choice k for the chooser i with x characteristic. $\rightarrow$ systematic term

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$\Rightarrow$ *The preferred choice is the one with the highest utility because both or either are high*

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$\Rightarrow$ *The* β *does not depend on on other values of y (other alternatives).*

Testing the main assumption:

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- Restricted model (a choice is removed) vs. unrestricted model (original)
- if IIA holds, then unrestricted model has smaller variance.

$\Rightarrow$ χ^2*-test with smaller value indicatee IIA holds.*

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$\Rightarrow$ *as in binomial regression, where you have one category vs. the rest*

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- The regression table
- Predicted probabilities (and comparisons/scenarios) for each category
  - as with binomial logit, one line per category
  - *cumulative* predicted probabilitites $\rightarrow$ illustrates tradeoffs

$\Rightarrow$ *Remember reference cateogry is* $1-$ *the sum of all other probabilities*

Specific visual interpretations

If you have three categories (if $M = 3$)

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$\Rightarrow$ *Illustrates tradeoffs*

The conditional logit

From the chooser's perspectives

The conditional logit holds the chooser constant, and considers alternative choices

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Mixing choosers and choices

The mixed conditional logit makes an interaction effect between choice-set variables and choice variables.

- Think hierarchical models with cross-level interactions