Conditional logits - models for nominal outcomes

Silje Synnøve Lyder Hermansen

2026-04-23

Introduction

Today: Nominal outcomes (again)

Strategies when our outcome variable is categorical

- categorical
  - multinomial regression
  - *conditional logistic regression*
- ordinal
  - ordinal regression

$\Rightarrow$ *Models of choice where we model the choice's characteristics*

Dependent variable: nominal

The discrete choice models describe mutually exclusive choices.

- The choice variable is nominal: we cannot rank it
- Our *appreciation* of it is continuous. Two sets of models:
  - Multinomial: Models *chooser* characteristics
  - Conditional logit: Models *choice* characteristics (today)

Discuss with your neighbour

Can you think of examples of research questions / data that focus on choice characteristics?

Two ways to understand conditional logit

Two ways to understand conditional logit

We will approach this in two ways:

- **Take 1:** Latent variable (utility) approach
- **Take 2:** Recoding + mini-regressions

$\Rightarrow$ Same model, different intuition

Take 1: Utility framework

Take 1: Utility framework

Each individual evaluates all options:

$$U_i(m) = w_{im}\delta + \varepsilon_{im}$$

- w_{im}: characteristics of option m
- δ: effect of these characteristics

Choice rule:

- Choose the option with highest utility

What does the model say?

- Options compete with each other
- Changing one option affects all comparisons

Example:

- If a party gets closer to you ideologically
- it becomes more likely *relative to all others*

$\Rightarrow$ Choice is inherently **comparative**

Key intuition

We are not modeling:

- "Who votes left?"

We are modeling:

- "Which option wins the comparison?"

$\Rightarrow$ Relative attractiveness drives outcomes

Take 2: Recoding the data

Take 2: Recoding the data

Instead of:

- one row per individual

We create:

- one row per **individual × option**

Outcome:

- $Y_{im} = 1$ if option m is chosen
- $Y_{im} = 0$ otherwise

What are we estimating?

We run:

- many small binary comparisons

Each row asks:
Was this option chosen or not?

$\Rightarrow$ Then aggregate across all options

Intuition: mini-regressions

Think of it as:

- comparing each option to its competitors
- within the same individual

$\Rightarrow$ A series of “within-choice-set” comparisons

Advantage: controls for context

Each comparison is made:

- within the same individual
- within the same choice situation

$\Rightarrow$ Automatically controls for:

- individual-level factors
- context of the choice set

Key requirement

Variables must vary:

- **across options**

Not enough:

- income, gender (same for all options)

Good variables:

- distance to each party
- candidate competence
- whether each party contacted you

Estimation and interpretation

Estimation

- preprocessing: declare "choice set"
  - that's the "grouping variable"
- use the `survival` package: `coxph()`

Interpretation: marginal effects

- there is no intercept, but probability of all choices sum up to 1
  - there is a "latent" propensity, but it depends on the size of the choice set
- you can interpret marginal effect
  - same as with binomial logits: partial scenario + backtransformation

Limitation

No variation within choice set:

- $\Rightarrow$ cannot estimate effect

Example:

- income is constant across all options

$\Rightarrow$ Drops out of the model

Limitation: size of choice set

The model relies on:

- comparing options within a choice set

Problems if:

- too many options
- too little variation

$\Rightarrow$ Works best with small, well-defined choice sets

Takeaway

- Conditional logit = model of comparisons
- Built from within-choice variation

Two ways to understand it:

- Utility maximization
- Recoded binary comparisons

$\Rightarrow$ Same model, different intuition

Discuss with your neighbour

We have seen 3 models of choice. Can you give each an identity card?

- when to use it
- data structure
- estimation technique
- how to interpret
- main assumption