

# Ordinal and Nominal Dependent Variables

## Applying MLE

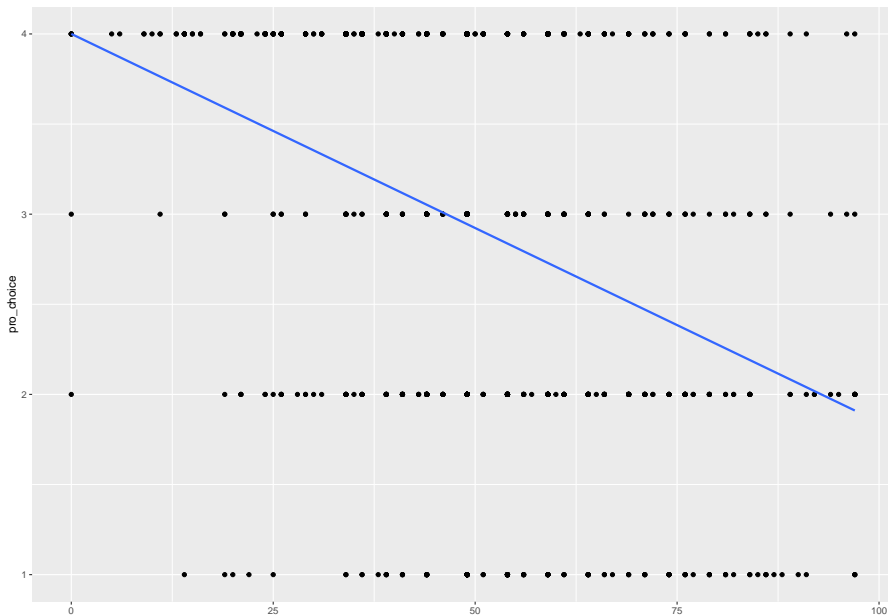
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# Ordinal Outcomes

- ▶ Ordinal variables have multiple categories
- ▶ They are ordered, but do not have meaningful distances between them – the numeric values have no inherent meaning
- ▶ We can imagine
  - ▶ a latent continuous variable  $y^*$
  - ▶ an observed variable  $y$
  - ▶  $y$  provides incomplete information about the underlying  $y^*$
  - ▶ different thresholds  $\tau$  on  $y^*$  translate to categories of  $y$ 
    - $y_i = 1$  if  $\tau_0 = -\infty \leq y_i^* < \tau_1$
    - $y_i = 2$  if  $\tau_1 \leq y_i^* < \tau_2$
    - $y_i = 3$  if  $\tau_2 \leq y_i^* < \tau_3$
    - $y_i = 4$  if  $\tau_3 \leq y_i^* < \tau_4 = \infty$

# Ordinal Outcomes – With OLS line



# Ordinal Outcomes – Assumptions

- ▶ To estimate with MLE, we must assume form of error distribution
- ▶ For order logit, we assume logistic distribution: mean=0, variance= $\pi^2/3$
- ▶ Calculate the probability that  $y = 1$ :

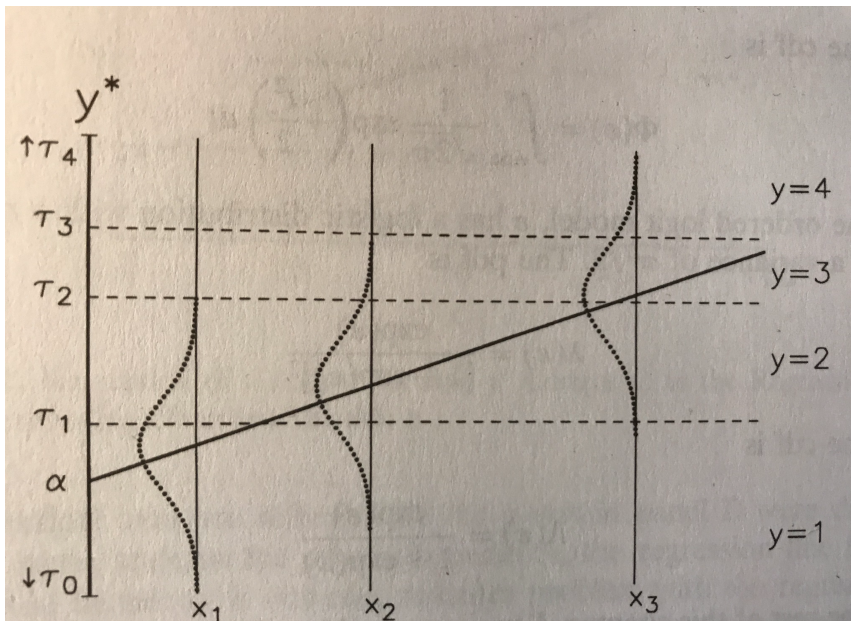
$$\begin{aligned}Pr(y_i = 1|x_i) &= Pr(\epsilon < \tau_1 - \mathbf{x}_i\beta|x_i) - Pr(\epsilon_i \leq \tau_0 - \mathbf{x}_i\beta|x_i) \\ &= F(\tau_1 - \mathbf{x}_i\beta) - F(\tau_0 - \mathbf{x}_i\beta)\end{aligned}$$

- ▶ Generally, the probability that  $y = m$  ( $m$  is the category of  $y$ : 1,2,3,4)

$$Pr(y_i = m) = F(\tau_m - \mathbf{x}_i\beta) - F(\tau_{m-1} - \mathbf{x}_i\beta)$$

( $F$  is the logistic or normal CDF)

# Ordinal Outcome Probabilities



# Ordinal Outcomes – Identification

- ▶ To estimate the model, we need to make further assumptions
- ▶ Note that we cannot estimate the  $\beta$ s and  $\tau$ s simultaneously – the model is unidentified
- ▶ To identify the model, we assume that  $\beta_0 = 0$  in order logit or that  $\tau_1 = 0$  in ordered probit
- ▶ This choice is arbitrary and does not affect the other  $\beta$ s or the probabilities

- ▶ To estimate the model, we maximize:

$$\begin{aligned}\mathcal{L}(\boldsymbol{\beta}, \boldsymbol{\tau} | \mathbf{y}, \mathbf{X}) &= \prod_{m=1} \prod_{y_i=m} Pr(y_i = m | \mathbf{x}_i, \boldsymbol{\beta}, \boldsymbol{\tau}) \\ &= \prod_{m=1} \prod_{y_i=m} [F(\tau_m - \mathbf{x}_i \boldsymbol{\beta}) - F(\tau_{m-1} - \mathbf{x}_i \boldsymbol{\beta})]\end{aligned}$$

( $F$  is the logistic or normal CDF)

# Nominal Outcomes – Multinomial Logit (MNL)

- ▶ Dependent variable is a set of nominal categories, with no order.
- ▶ The approach is to simultaneously estimate binary logits for all possible comparisons among the outcome categories.
- ▶ The advantage of the MNL is that the sample is used more efficiently.
- ▶ To do this, it is necessary to establish a **baseline choice** category (usually  $m=1$ ), whose parameters are constrained to be 0.



# Nominal Outcomes – Assumptions

- ▶ Assume a logit function to have probabilities of outcomes constrained between  $[0;1]$
- ▶ And constrain  $\beta_1$  to 0
- ▶ The probability of observing outcome  $y = 1$  is:

$$\begin{aligned} Pr(y_i = 1|x) = \pi_{i1} &= \frac{\exp(x_i\beta_0)}{\exp(x_i\beta_0) + \sum_{k=2}^M \exp(x_i\beta_k)} = \\ &= \frac{1}{1 + \sum_{k=2}^M \exp(x_i\beta_k)} \end{aligned}$$

(where  $k$  are the remaining, unconstrained outcomes)

- ▶ Then for the remaining (unconstrained) outcomes  $m$ :

$$Pr(y_i = m|x) = \pi_{im} = \frac{\exp(x_i\beta_m)}{1 + \sum_{k=2}^M \exp(x_i\beta_k)}$$

- ▶ Maximize the likelihood function:

$$\mathcal{L} = \prod_{y_{i1}=1} \pi_{i1} \prod_{y_{i2}=1} \pi_{i2} \cdots \prod_{y_{iM}=1} \pi_{iM} \quad (1)$$

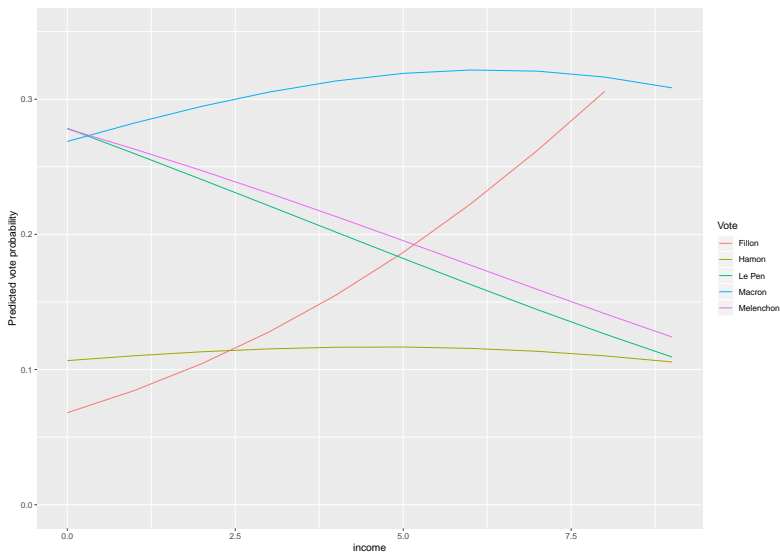
$$\mathcal{L} = \prod_{i=1}^N \prod_{m=1}^M \pi_{im}^{y_{im}} \quad (2)$$

# Predicted Probabilities

- ▶ The neatest way to communicate our results for continuous predictors is to demonstrate the **predicted probabilities** of a given predictor,
- ▶ Other predictors are held constant (usually at their mean or other logical value)
- ▶ In R, we define a data frame, mandating the values of the  $x$ s at which we wish to estimate the probabilities
- ▶ We keep all but one constant. We vary the predictor of interest logically
  - ▶ From its minimum to maximum
  - ▶ From  $\text{mean}-\text{sd}$  to  $\text{mean}$  to  $\text{mean}+\text{sd}$
  - ▶ Or over some key values of interest

# Example

## Explaining vote in 2017 French presidential election



# Warning: Independence of Irrelevant Alternatives

- ▶ MNL is based on an assumption that the decision between alternative 1 and alternative 2, for example, is independent on all other alternatives.
- ▶ In our case, whether a voter supports say Macron over Hamon is assumed independent on Melenchon.
- ▶ This is called the **Independence of Irrelevant Alternatives** or IIA assumption.